CENTERS ALL THE WAY DOWN: A STUDY OF CENTRALITY IN THE MODERN CITY

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CENTERS ALL THE WAY DOWN: A STUDY OF CENTRALITY IN THE MODERN CITY

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. . . the city is an interface of scales . . .

– Dr. John Peponis in conversation with the author

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SUMMARY

In this paper, a kernel density estimation analysis of commercial and office land uses in Atlanta reveals a two level logic of centrality. First, higher kernel density volumes are more associated with areas with denser street connectivity. That is, more important centers are associated with more densely intersecting street networks. Second, within their area of dominance, centers tend to be associated with longer streets intersecting a good number of other long streets (high directional reach at two direction changes). This two level logic leads to a non-uniform pattern of centrality where centers of higher order tend to gravitate towards major thoroughfares and be surrounded by centers of lower order. Within this overall pattern, some locations, mostly inside I-285 are associated with a wide range of choices of accessible centers of different scales while other locations, mostly outside I-285 are associated with a limited range of choices of higher order accessible centers.

CHAPTER I

INTRODUCTION

In *A Brief History of Time* (Hawking, 1998), Stephen Hawking describes an interesting encounter:

> A well-known scientist (some say it was Bertrand Russell) once gave a public lecture on astronomy. He described how the earth orbits around the sun and how the sun, in turn, orbits around the center of a vast collection of stars called our galaxy. At the end of the lecture, a little old lady at the back of the room got up and said: "What you have told us is rubbish. The world is really a flat plate supported on the back of a giant tortoise." The scientist gave a superior smile before replying, "What is the tortoise standing on?" "You're very clever, young man, very clever," said the old lady. "But it's turtles all the way down!"

This oft-quoted story is used to poke fun at those who carry strange beliefs without empirical proof. The notion that the world rests on the back of a turtle is absurd. And yet, hidden within the story is another lesson. While the scientist disregarded any concept of a deeper meaning beneath the world, the old woman's belief reflected a more complex understanding of the world. To her, the world rested upon a layer of meaning, which rested upon another layer of meaning, which rested upon further layers of meaning, "all the way down." While the scientist dutifully cut away excess meaning, the woman looked deeper and found a recursive relationship of meaning that better explained her experience of the world.

So it is with cities. When we travel from home to work, when we visit the grocery, when we go out for a pint of beer, we move between places with vastly different scales of activity, and levels of privacy and connection. We may work in a dense downtown that forms a center of an entire metropolis, and on our way home we may stop for groceries in a commercial district around which our district of the city centers. Then, in the evening, we may stroll to a caf that forms a neighborhood-scale center of activity. In all of our life in cities, we interact with the city at different scales of activity, in areas of different intensity of activity. This reflects a fundamental aspect of the modern city: it contains an uneven surface of attraction, with some places highly active and others very private. These "attraction inequalities" form a system of centers in a nested hierarchy of scales; some centers exert global pull, while others are only significant at the smallest scale. The structure of this pattern of centrality is fundamental to the experience and function of places within a city. By looking deeper and wider within each center, a further layer of centers appears, until one discovers that the meaning and structure of the city is centers, all the way down.

This thesis will empirically examine the distribution of centers of commercial activity in Atlanta, chosen as a particular example of the modern city. Using a detailed dataset containing measures of built space for different types of activity, we will map the distribution of commercial activity in order to perceive the hierarchy of centers distributed throughout Atlanta. Our analysis of this dataset, using kernel density estimation, will estimate the intensity of commercial activity at multiple scales. We will then perform several quantitative and qualitative analyses on the set of centers with the hope of showing objectively that Atlanta's hierarchy of centers fits with notions of centrality described by Constantinos Doxiadis, Christopher Alexander, and Bill Hillier. By looking beneath the surface of the city, into the layers of centers all the way down, we hope to arrive at a better understanding of the patterns of form and activity and illuminate the meaning of the city itself.

CHAPTER II

LITERATURE REVIEW

We are by no means the first to study the pattern of centers in cities. Indeed, we follow a long series of urban theorists who believed that understanding centrality, the tendency for places in space to organize hierarchically, was essential to understanding cities. Though centrality has been an important concept for researchers of urban form for centuries, quantitative definitions of centrality did not emerge until the twentieth century. Christaller's Central Place Theory, first presented in 1933, was one of the first, extrapolating the one-dimensional demand curve of microeconomics into space. Central Place Theory eventually encouraged responses from forward-looking urban theorists such as Constantinos Doxiadis (Doxiadis, 1968) and Christopher Alexander (Alexander et al., 1987), each of whom proposed different theories of urban centrality as solutions to contemporary urban problems. While Doxiadis hoped to solve the problems of massive urban growth and the destruction of historic centers from new development, Alexander hoped to reform the process of urban growth so that it produced places with “wholeness”.

Over the last thirty years, Bill Hillier and other researchers have sought to develop a comprehensive theory of urban form and function through Space Syntax. Space Syntax uses configurational measures of urban form to point toward a theory of the production and function of urban centrality. The measures used by Space Syntax researchers are able to measure urban form on multiple scales, providing a powerful tool for understanding how the structure of road networks forms “an interface of scales” (Peponis, 2011) between locations in the urban fabric.

By developing a process for measuring and analyzing urban centrality, we hope to draw both on previous theories of centrality and new tools developing for measuring the distribution of elements in the urban fabric. In this section we will give a concise background of the precedent for studying urban centrality and the theoretical basis for the analysis that follows. We then will describe other recent studies of commercial location. Finally, we will discuss other analyses of Atlanta's urban form, both quantitative and qualitative, as a background to the specific study area.

2.1 Theory of Urban Centrality

Centrality is best described in context of space in the city. As Bill Hillier notes, urban space is formed by "spatial and spatio-functional laws" that are both easily intuited and objective and mathematical (Hillier, 2009). One of these laws is that urban space is organized so as to provide access from all parts of a densely developed area to all other parts. Patterns of accessibility and land use, however, converge onto certain areas which act as concentrations of intense activity and as reference points for circulation and orientation. Thus, we can speak of urban space as having one or more centers.

2.1.1 Central Place Theory

Christaller and Lösch formulated Central Place Theory as one of the first quantitative explanations of urban centrality. In *The Economics of Location* (Lösch, 1954), Lösch showed that market areas, the area over which a firm distributes its goods, are determined by economic forces. Beginning with one-dimensional demand curves, Lösch extrapolated to two dimensions to show that in an undifferentiated region, market areas form a regular pattern of hexagons. Since different products have different levels of demand, market areas exist at various sizes. Lösch and Christaller proposed that the market areas form a strong hierarchy, such that larger central places dominate smaller central places. This hierarchy is described by k, the number of smaller places dominated by each larger place. For $k = 3$, the arrangement forms a neat symmetry,

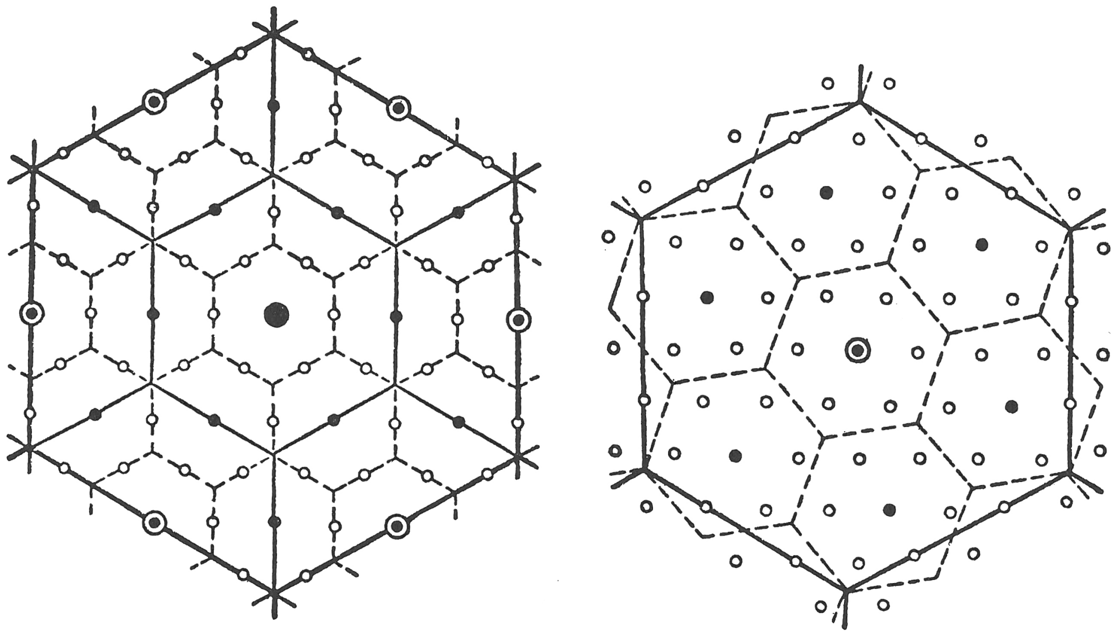

Figure 1: Lösch proposed several model distributions for regional structure, with each defined by k, the number of places dominated by each larger place. Shown here are $k = 4$, left, based on the communication principle, and $k = 7$, right, based on the political principle. (Lösch, 1954, p. 132)

such that all smaller centers locate midway between similarly sized larger centers. Christaller proposed that this was the most efficient distribution. That is, it followed the "supply principle" (Lösch, 1954, p. 133). Other distributions are also possible, following other forces. For example, $k = 4$ follows the communication principle, and $k = 7$ follows the political principle.

Central Place Theory remains a strong economic explanation for the distribution of commercial activity in space. It is a particularly useful theoretical basis for this study because it proposes that different scales of commercial activity form centers in a hierarchy of scales. We will see this illustrated in our derivation of a system of centers for Atlanta. However, a criticism of Central Place Theory is that it assumes each consumer travels to the nearest store to make a purchase. In reality, purchasing patterns are more complex, as noted by Christopher Alexander, who argued that hierarchies tend to form overlapping lattice-like structures. (Alexander, 1965)

Lösch and Christaller acknowledge that the distributions they describe assume an idealized, featureless plane. Doxiadis and Alexander take a different approach, proposing normative distributions intended to solve contemporary problems.

2.1.2 Constantinos Doxiadis and *Ekistics*

In *Ekistics* (Doxiadis, 1968), Constantinos Doxiadis proposed a new science of human settlements, ekistics. Following World War Two, the continuing growth of cities in both complexity and size necessitated a new way of studying human settlements and their problems. Doxiadis began by proposing two classifications: a size framework reflecting all human settlement, from the individual to the global city ("ecumenopolis"); and a framework of elements common to all cities – nature, society, shells, networks, and culture.

After introducing the two frameworks used in his study, Doxiadis began to explain his theory of Ekistics. Doxiadis divided all human settlement into scales based on his size framework and then showed how "communities and ekistic units are organizationally related to each other in a hierarchical manner." (Peponis, 2003) The particular form of a settlement is determined by both a tendency to keep all parts near all parts (a centripetal force) and by a tendency to grow along major roads (a linear force). Doxiadis noted that "any attempt to formulate and elaborate the laws that govern settlements must not aim at simple laws of cause and effect but rather at statistical laws of effect and chance." (Peponis, 2003)

Doxiadis described human settlement patterns as the result of forces responding to human needs. Chief among these needs is the dual need to be both near other people and yet not too close. As Doxiadis described, human settlement patterns are in tension between these two needs. These needs apply not only to people, but also to the functions of cities: providing for human needs. He compared the pattern of settlement formation to the distribution of people around an orator – first all come

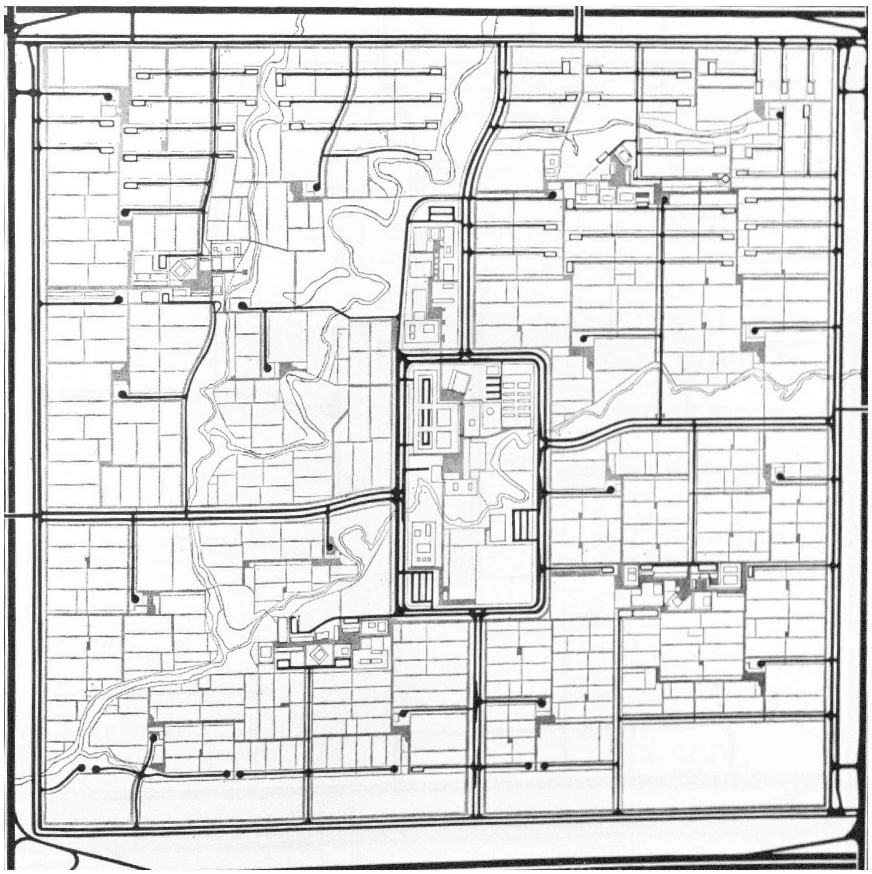

Figure 2: Doxiadis's concept of the "static cell" was fully developed in his plan for Islamabad. This image from Doxiadis (1968).

very close, but as the crowd grows it settles into a comfortable equilibrium, neither too close not too far. (Doxiadis, 1968, p. 333)

To Doxiadis, historical settlement patterns, whether natural, radial, monumental, or Utopian, approached this equilibrium more quickly than forces changed the settlement pattern. These cities were "static cells". Cities of the mid-twentieth century, however, were dynamic settlements. Growth occurred at a faster rate than a settlement could reach equilibrium. Constant change disrupted these static cells, forcing the redevelopment of traditional, organic centers. He wrote that the modern city's "center is forced to grow like a cancerous growth, eating into those cells of the city which are close to it, transforming them from residential to commercial areas, changing their functions, contents, structure, etc. This is the main problem of a city becoming a Dynapolis, and this process becomes intensified as the city continues to grow." (Doxiadis, 1968, p. 364)

Seeing no alternative from his contemporaries that took account of the forces creating the modern, dynamic settlement, Doxiadis proposed an alternative vision, which he labeled a *Dynapolis*. The Dynapolis was a model for a dynamic city composed of many static cells. As growth occurred, new static cells would be constructed along a chosen linear axis. Over time the city would grow in one direction, away from the historic center, in a form Doxiadis labeled "uni-directional" (Doxiadis, 1968, p. 365). As the Dynapolis grew, the original transportation arteries would be removed from the old center and reconstructed on the edge of the city, allowing the older centers to remain static.

Doxiadis's static cells were designed to prevent future change by removing through-traffic. The result was to be a flourishing of its inner life:

> By removing the main circulation networks from within the cells, we can help the latter remain static and consequently much more directly related to the growth of natural phenomena. Such static cells are no longer subject

> to continuous internal changes. They provide Man and Society with time in which to relate themselves to Nature and to changing functions. Growth is thus guided toward a repetition of such static cells, as in most cases in Nature, and to the development of specialized cells (specialized Ekistic units) for specialized functions. (Doxiadis, 1968, p. 357)

Thus, Doxiadis believed that the ultimate vitality of urban life depended on the isolation of static cells from constant change, resulting in the flourishing of their culture.

However, Doxiadis did not believe that merely growing along a predetermined axis would solve the problems of the Dynapolis. Constant growth would still require the destruction of existing orders. Neither did he accept decentralization as a solution – it merely served to deprive the residents of new towns from the services of existing centers. Rather, Doxiadis proposed a "new centralization." (Doxiadis, 1968, p. 375) Ultimately, the Dynapolis must join with other Dynapoli to form a *Dynamegalopolis*. Within a Dynamegalopolis, centers would be created of a higher scale than the existing Dynapolis along with a new, higher-order transportation network. The new centers would occur at some distance from existing centers, and the new circulatory network would join existing centers in a way that drew growth to new centers.

Finally, when the pressures of growth overwhelmed the Dynamegalopolis, an even higher-order system would be created. The *Ecumenopolis* would be a world-wide, static network of cities. As Doxiadis described "In this way the growing Dynamegalopolis gradually leads to Ecumenopolis, which will be relatively static as was the polis. During the phase of Ecumenopolis humanity will once again reach a period of relatively static balance between all the elements of the settlements." (Doxiadis, 1968, p. 376)

Ekistics is very relevant to our current study, providing two contributions. First,

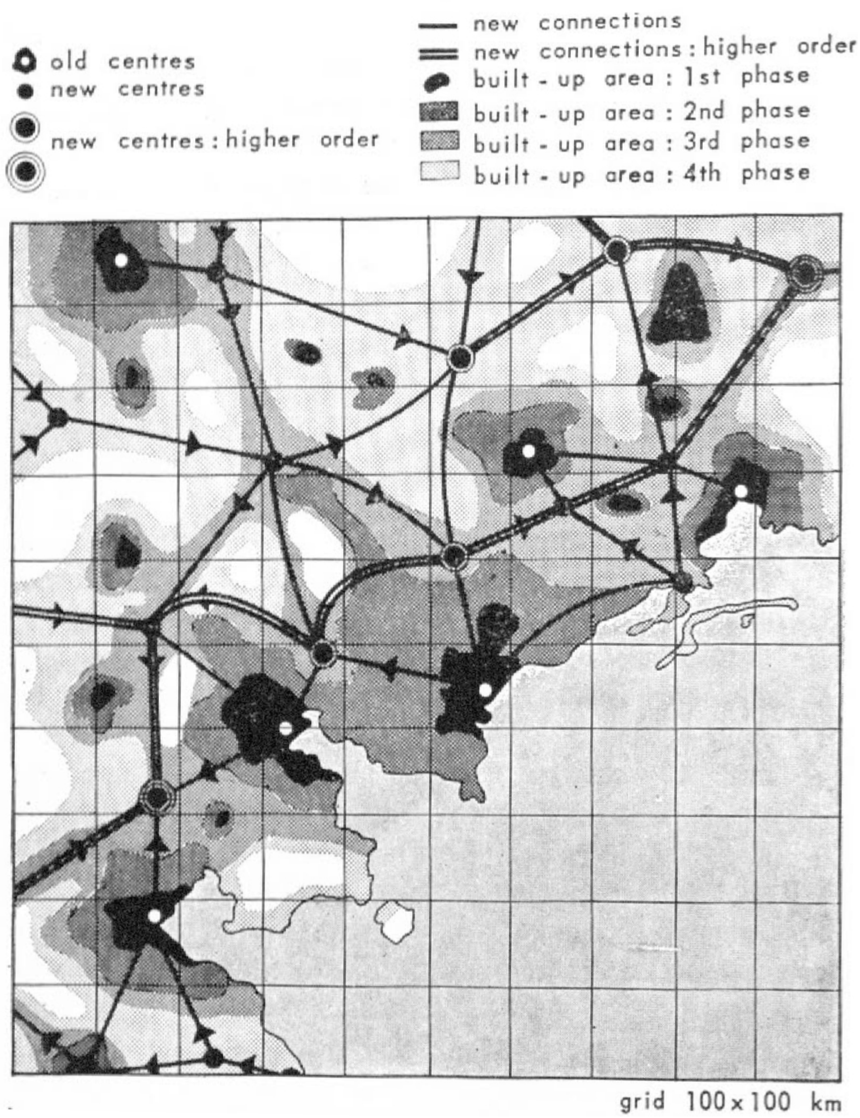

Figure 3: The dynamegalopolis was Doxiadis's plan for the eventual merger of multiple dynapoli along the path of new infrastructure as shown here. This image from Doxiadis (1968).

Doxiadis's description of the processes of urban growth provides a basis for our analysis and a foundation for why we might expect the distribution of commercial centers to be significant to the nature of a city. For this, his theory is second only to Hillier's "Centrality as a Process." Second, Doxiadis, along with Koolhaas's essay and Haynie's historical analysis of Atlanta, helps provide a conceptual baseline for Atlanta's structure. In some ways, Atlanta seems to be Doxiadis's proposal made manifest – growth in Atlanta often occurs linearly, in an ever expanding line of centers. Furthermore, these centers are drawn to large infrastructural investments of the same sort Doxiadis described to encourage the formation of the Dynamegalopolis. Our analysis in chapter 4 will examine the connection between Atlanta's freeway infrastructure and commercial centers.

2.1.3 Christopher Alexander

Christopher Alexander proposed a structure of centers as well, but his proposal differs from Doxiadis's proposal for discrete centers, proposing instead that development should form an interconnected network of centers at multiple scales. In *A New Theory of Urban Design* (Alexander et al., 1987), Christopher Alexander attempted to formulate a series of rules to govern the creation of urban design. Alexander saw that different urban actors held contradictory and often harmful views on urban design; for example, "the welfare department is trying to build houses at low cost to help poor families. The department of transportation is trying to speed traffic flow in the city. City officials are concerned with keeping disparate functions separate by means of the zoning ordinance," (Alexander et al., 1987, p. 20) and so on. Alexander viewed this division of responsibility as harmful to the city as whole, because individual actors did not consider the health of the whole city when they acted.

To remedy this problem, Alexander proposed a series of rules that would accomplish the ultimate goal, "the creation of wholeness in the environment." (Alexander et al., 1987, p. 22). First, he proposed a single, overriding rule: "Every increment of construction must be made in such a way as to heal the city." He explains further that the city is an overlapping network of "wholes", and therefore "Every new act of construction has just one basic obligation: it must create a continuous structure of wholes around itself.". This system of wholes is defined by a "field of centers", generated incrementally, such that every new center also generates at least one center at a larger scale, other centers at the same scale, and more centers at a smaller scale. He later defines this concept as a rule for urban design, saying "Every whole must be a 'center' in itself, and must also a produce a system of centers around it." [p. 92]. Thus Alexander argues that wholeness, itself his ultimate determinant of urban vitality, is the result of an interconnected network of centers at many scales.

Alexander defines "centers" broadly, as an object or space composed symmetrically of other centers such that all parts are interrelated. Thus at different scales a center could be a doorknob or an entire city. At many scales larger than individual buildings but smaller than entire cities, a center is composed of agglomerations of buildings and urban spaces. This is the scale at which most study of urban design focuses, and it is the scale we examine in our analysis below.

2.1.4 Space Syntax and "Pervasive Centrality"

Space Syntax, as developed by Hillier, Peponis, and Hanson, has become a theory of urbanism that points toward a process and rationale for the production and function of urban centrality. Space syntax is less normative than the theories of Doxiadis or Alexander. It is also less abstract than Central Place Theory. Where Central Place Theory was derived from the one-dimensional demand curves of microeconomic theory, the theory of centrality promulgated by Space Syntax was developed in light of measurements of urban structure, such as integration and reach, found to correlate closely with actual behavior. Thus it relies heavily upon inductive reasoning – observing first and formulating a theory after. It provides an excellent theory of why urban space forms "attraction inequalities" (Hillier, 1999) that produce commercial centers. This theory of urban centrality is particularly well explained by four articles written by Bill Hillier, "Centrality as a Process (Hillier, 1999), "A Theory of the City as Object" (Hillier, 2002), and "The Golden Age for Cities?" (Hillier, 2006).

2.1.4.1 Centrality as Process

In "Centrality as a Process", Hillier attempted to determine the process which causes "live centrality," that form of urban centrality that includes retail, markets, and entertainment. Live centrality is particularly well correlated with high levels of movement (as opposed to the institutional, office, and governmental forms of centrality), so it should be explainable using Hillier's theory of "movement economy" (Hillier, 1996a). Hillier proposed that configuration generates attraction, and therefore "the appearance of attraction inequalities in the urban surface is to be accounted for by the spatially driven movement economy process."

Hillier discussed centers broadly, mentioning how they develop, how subcenters form, and how urban growth tends to shift centers toward the edge of cities. Because centers constantly change, it is necessary to understand centrality as a process, rather than as a state at a point in time. Hillier then made several examinations ("heuristics") of the axial maps of London and York, England in an attempt to detect the process in operation. He noted that several large centers occur on globally well-integrated streets in the locations where block density is highest, but he also notes that many smaller centers are undistinguished in terms of global integration. Then, stepping street-by-street through neighborhoods where he knows subcenters exist, he showed the pattern of streets two-levels deep. Less important streets are poorly connected within the neighborhood, but high streets tend to integrate the entire neighborhood. This pattern recurs throughout London for various neighborhood high streets.

Hillier then described research performed by Maria Adriana Gebauer-Munoz using the location of retail in the Camden borough of London. She performed a multiple regression using the natural log of the number of retail shops, restaurants, and entertainment outlets as the dependent variable. Her notable result was that while global integration correlated poorly with the number of shops, a measure of local integration (performed two levels deep from the "shopping segment" of the axial line) correlated stronger than any single other variable. Hillier concludes that "local grid conditions are shown to be the key variable associated with the degree of local centrality."

After exploring the axial map of York at a larger scale, Hillier concluded that centrality is a function of both local and global processes. Global processes decide where a center will form, while local processes guide the intensification of the center's grid, as described in Siksna (1997), in order to allow interdependence and interaccessiblity. Hillier then described this process in more technical detail, beginning the analysis that is developed more fully in "A Theory of the City as Object" (Hillier, 2002).

2.1.4.2 A Theory of the City as Object

In "A Theory of the City as Object" (Hillier, 2002), Hillier continued developing the theory he developed in previous work: "Natural Movement" (Hillier et al., 1993), "Cities as Movement Economies" (Hillier, 1996a), and "Centrality as a Process" (Hillier, 1999). These papers developed Hillier's theory that city form develops as an outcome of the patterns of movement, both within the city and into and out of the city. He described a process by which the patterns of movement result in a city's form. In this paper he attempted to explain how form is the outcome of several spatial laws. Comparing the axial maps of cities from different cultures, he found that global structure in each is a constant, represented by microeconomic forces, but that local structure varied, determined by socio-cultural forces.

After examining the basic generative process used to generate synthetic cities in his previous work, *The Social Logic of Space* (Hillier and Hanson, 1984), Hillier performed several experiments with the process. These experiments managed to generate forms that resembled organic cities in some senses, but lacked the "deformed wheel" structure found in the cities examined previously, where long, well-integrated paths extended outward from a central hub, with less integrated neighborhoods spread between. In order to find the deficiencies of the basic generative process, Hillier next began performing experiments on how the arrangement of blocks on a line or on a plane affects the universal distance of a given configuration. (Universal distance is the sum of the distances from every possible origin to every possible destination.) These experiments build on work described previously in *Space is the Machine* (Hillier, 1996b). Hillier concluded that two laws describe how objects placed in space affect universal distance: the law of centrality and the law of compactness. The law of centrality states that universal distance is minimized (and metric integration is maximized) by placing objects to conserve longer lines at the expense of creating short lines. The law of compactness states that placing compact, less elongated forms increasing universal distance less than placing more elongated forms.

Hillier then applied these laws to the generative process with two conjectures. First, local structure is determined by a culturally-determined "interaccessiblity parameter" that operates on the residential process (which is driven by socio-cultural forces) using the compactness law. Second, "with the growth of the settlement... the public space process, led by micro-economic activity, sets a global interaccessibility parameter working through the centrality law." Furthermore, the centrality principle has a dual effect, creating both integration globally and segregation locally: "The public space process thus tends to generate the local-to-global deformed wheel structure at whatever level of the settlement it is applied.... In its loci of most concentrated activity it will generate not a linear system which minimizes universal distance in the system as a whole, but a locally intensified grid which minimizes movement from all origins to all destinations in the local region." Thus, the dual process of micro-economic and socio-cultural forces which shape a city achieve a single expression in the law of centrality.

2.1.4.3 The Golden Age for Cities?

Hillier's brief essay, "The Golden Age for Cities?" (Hillier, 2006), explained the reasons for the sort of research performed by Space Syntax – it helps explain the "generic form of cities, in the hope that, once this was understood, we would be able to detect the effect on the city of other factors." This research showed that "cities tend to evolve towards a generic dual form: a network of linked centres at all scales (from a couple of shops and a caf through to whole sub-cities) set in a wider background of residential space." Thus, future cities are likely to retain this generic form, with small changes in the level of movement and co-presence of activity based on future needs.

Hillier then suggested several major areas for future research. First, the overall relationship between self-organizing processes and conscious design and planning should be studied so that designers and planners are better able to "create interventions that work with self-organizing processes, and go with the natural flow of cities."

Hillier then added that the interdependent relationship between part and whole is only beginning to be understood. It is clear that many "evolved" cities exhibit a sense of being both in a small-scale place as well as a large-scale city. But what is not clear is how these two scales manage to develop out of the incremental growth of the city. Hillier proposed research studying how to create places that fit in both the local and global context of their surroundings.

2.1.4.4 Hillier's work as a guiding theory

Hillier's theory of centrality is well summarized by by the following quote from the presentation *Using space syntax to regenerate the historic cores of cities: the case of Jeddah* (Hillier et al., 2008):

> This leads us to a new definition of the spatial form of cities. Cities in general - and not just 'organic' cities - self-evolve into a foreground network of linked centres at all scales, from a couple of shops and a caf through to whole sub-cities, set into a background network of largely residential space. Good cities, we suggest, have pervasive centrality in that centrality functions diffuse throughout the network. The pattern is far more complex than envisaged in theories of polycentrality. Pervasive centrality is spatially sustainable because it means that wherever you are you are close to a small centre and not far from a much larger one.

Hillier's work provides both the theory necessary and the impetus for this research. Together, his work explains both the structure of centrality in the city – "a network of linked centres at all scales set in a wider background of residential space" – and the reason for such a structure – that centers form because of the interaction of local and global forces, demonstrated by local and global syntactical measures. This paper is therefore an attempt to apply Hillier's understanding of urban centrality to Atlanta in order to better understand the forces that generate centrality in the modern city.

2.2 Recent Studies on Retail Location

Though our analysis described below uses a set of commercial and office land uses as data, this paper is intended not to present a detailed analysis of retail location, but but to describe a broader measure of activity intensity, reflecting a wider set of activities related to urban centrality. Therefore our work is not a work of retail location theory. Nonetheless, it is quite similar to several other recent studies that compared retail shop locations to measures of urban network structure, whether derived from graph theory or Space Syntax. Their methods and conclusions are quite relevant to our study, and so they are discussed below.

2.2.0.5 Street Centrality and Densities of Retail and Services in Bologna, Italy

In "Street Centrality and Densities of Retail and Services in Bologna, Italy" (Porta et al., 2009), Porta performed an analysis similar to the one performed below, examining the correlation between retail location and measures of urban centrality in Bologna, Italy. He hypothesized that centrality should strongly predict the location of retail and service activities. Rather than using space syntax metrics, Porta used metrics from multiple centrality assessment (MCA), as explained in Porta et al. (2006) and Crucitti et al. (2006). These measures include closeness centrality, CC, betweenness centrality, CB, and straightness centrality, CS, each calculated on networks of edges and nodes. Closeness centrality measures the distance from each node in the network to every other node, rather like integration in space syntax. It is a measure of accessibility. Betweenness centrality measures the extent that the shortest paths between other nodes cross a given node. Straightness centrality measures how easily a node can be reached directly, on a straight line, from other nodes. These metrics are calculated differently than the metrics of space syntax, but the concepts they measure are similar. Porta computed them for Bologna using a C++ script.

Porta used these metrics as independent variables in a bivariate regression with two possible dependent variables: number of retail shops and number of both retail and service outlets. In order to correlate he converted each of these variables to a common raster format using kernel density estimation (KDE). KDE is a method for interpolating the location of each variable in space by estimating their density using a kernel function. A KDE analysis occurs over a neighborhood defined around every point in the analysis, referred to as the bandwidth. KDE will be more fully explained below. Porta used three bandwidths, 100 m, 200 m, and 300 m, for a total of thirty separate regressions.

His results indicated a strong correlation between centrality metrics and location of commercial uses in Bologna. His top fifteen regressions had Pearson correlation coefficients greater than 0.500, with the strongest correlation between global betweenness centrality and combined retail and service activities with a bandwidth of 300 m. In fact, betweenness centrality repeatedly showed the strongest correlation with commercial location in Bologna, followed by closeness centrality. Porta's results also showed a stronger correlation when a larger bandwidth is used.

2.2.0.6 Path and Place: A Study of Urban Geometry and Retail Activity in Cambridge and Somerville, MA.

Andres Sevtsuk's recent PhD Dissertation, *Path and Place: A Study of Urban Geometry and Retail Activity in Cambridge and Somerville, MA.* (Sevtsuk, 2010), attempted to answer a similar question as the work of Campo and Porta. Using a dataset containing the locations of every retail establishment in Cambridge and Somerville, Massachusetts, Sevtsuk sought to determine whether the spatial configuration of the environment affected the location choices of retail establishments. Unlike Porta and Campo, Sevtsuk used a spatial econometric model, the strategic interaction framework. The model allowed Sevtsuk to separate the effects of spatial autocorrelation from effects due to spatial configuration. His work joined retail location theory, typically studied by economists, with configurational studies of the built environment, usually the province of planners and architects.

Sevtsuk described urban form using measures from graph theory: reach, remoteness, and betweenness. Sevtsuk's measure of reach differs from our similarly named measure described later. Sevtsuk's reach measure computed the amount of building volume, number of jobs, or number of residents within a given radius of analysis. Remoteness measured the average distance to one of those quantities for the set of all items within a given radius. For example, remoteness of residents measured the average distance from a building to each resident within a given radius. Sevtsuk also calculated remoteness using other measures of distance – turns and intersections. Betweenness, a measure first devised for graph theory by Linton Freeman (Freeman, 1977), is the fraction of shortest paths from each location in a network to each other location in that network that pass through the chosen location.

Sevtsuk's primary analysis included each of these measures of urban form, several urban design variables (sidewalk width, street width, and number of adjacent streets per parcel), and measures for spatial autocorrelation, as independent variables in an ordinary least squares multiple-regression model with a binary dependent variable indicating whether each building contained a commercial establishment. His analysis showed a strong tendency for spatial clustering of retail activity, but many other variables had significant effects as well. There was a substantial tendency for retail space to locate near jobs and away from residences. The variables measuring turn remoteness (which are similar to configurational measures like integration) were generally insignificant, with one exception. Turn remoteness from subway stations showed a small negative effect, indicating that retail prefers to locate near transit. Intersection remoteness showed a similar effect. However, betweenness had a very large positive effect, indicating that retail activity greatly prefers locations along well-connected routes. Several urban design variables produced a noticeable effect as well – building height had a negative effect, sidewalk width had a positive effect, and roadway width had a negative effect. However the strongest effect overall, with a larger t value than even the spatial autocorrelation term, was the variable measuring the number of adjacent streets. That is, retail land uses strongly prefer a location on a corner.

2.2.0.7 Retail shop distribution in interrupted orthogonal grids: The case of Tijuana

Leonardo Campo's masters thesis, *Retail shop distribution in interrupted orthogonal grids: The case of Tijuana* (Campo, 2007), is similar to Porta's study of Bologna. Campo applied Space Syntax measures to analyze the distribution of retail shops in Tijuana. Using a set of locations derived from field surveys, he described the way retail clustered into centers of different scales around more integrated streets. Campo used three measures of urban form: integration, choice (similar to the betweenness measure used by Porta and Sevtsuk), and int-choice, a measure synthesized from integration and choice. He described the relationship between the form measures and the distribution measures thoroughly, concluding that "the evidence...suggests that the global structure, nicely highlighted by both global choice and integration, seems to be driven by the way that...isolated orthogonal grids are embedded within the overall area... Once it is in place the local geometric and syntactic properties, for most cases, for each urban grid determine the size, diversity, and direction of shop distribution." (Campo, 2007, p. 45)

He then performed a quantitative analysis, comparing integration, choice, and a combination integration-choice measures at different radii against the density of retail shops on a given street segment. He found that each of the three measures of urban form had higher correlations to shop density at lower radii, which indicated that, as Hillier suggests, the intensification of a local street grid is a primary driver for intensification of retail activity.

2.2.0.8 Summary

These three studies each found that measures of urban form correlated with the location of retail land uses in their studied cities. While Porta and Sevtsuk found strong correlations using generic measures such as betweenness, Campo produced strong correlations using measures from Space Syntax, such as integration. It is clear that quantitative studies of urban centrality, while full of historical precedent, are not well established. Analytical methods and techniques for measuring urban form are still being debated. Sevtsuk's more recent work uses rigorous econometric methods, while Porta's and Campo's work use linear regression through different methods of joining measures of urban form to measures of retail activity. Our analysis, described in chapter 4, will use similar methods to Porta's work, but with yet another method for joining urban form variables to commercial activity variables. We will also use different measures of urban form, choosing neither the generic measures of Porta and Sevtsuk, nor the integration of Campo, but the metric reach and directional reach measures developed at Georgia Tech. Our analysis of Atlanta will contribute an additional study to this small but growing area of research.

2.3 Related Studies of Atlanta

Several prior works describing the urban form of Atlanta provide a better understanding of how Atlanta applies to the study of centrality. In *S, M, L, XL* (Koolhaas and Mau, 1995), Koolhaas critiqued Atlanta harshly,arguing that it lacks the usual structure of cities. "Atlanta does not have the classical symptoms of city; it is not dense; it is a sparse, thin carpet of habitation, a kind of suprematist composition of little fields. Its strongest contextual givens are vegetal and infrastructural: forest and roads. Atlanta is not a city; it is a landscape." Koolhaas argues that, while most cities have a center and an edge in opposition, in Atlanta, "there is no center, therefore no periphery. Atlanta is now a centerless city or a city with a potentially infinite number of centers." Koolhaas then critiqued John Portman, arguing that Peachtree Center, which seemed intended to revive downtown instead lead to a proliferation of imitations, distributed in new centers outside of downtown. He concluded by saying Atlanta is Frank Lloyd Wright's Broadacre City made manifest and John Portman is "disurbanist to the world".

Koolhaas's critique is biting and widely-circulated. However, his diminishment of Atlanta as disurban is unjustified, and likely reflects only a cursory knowledge of the city. Viewed from the freeway, Atlanta appears to be a landscape, a picturesque visual image. In reality, Atlanta has a complex urban structure with logic similar to other large urban areas. Where Koolhaas claimed a lack of urban structure, we will reveal it, showing that Atlanta too is a product of organized complexity.

In contrast, researchers at Georgia Tech have produced a number of studies applying space syntax to Atlanta and providing a wealth of background about its urban form. In "The Effects of Street Connectivity upon the Distribution of Local Vehicular Traffic in Metropolitan Atlanta" (Scoppa et al., 2009), Scoppa, French, and Peponis compared average daily traffic volume with a number of spatial variables, including several measures of metric reach and directional distance, metric betweenness, distance from city hall, and street width. The strongest bivariate correlation for a syntactic variable ($R^2 = 0.199$) was between traffic volume and directional distance with two direction changes. They also performed several multivariate regressions, finding the strongest correlation ($R^2 = 0.550$) using street width, five mile reach, and distance from city hall as independent variables.

The authors' analysis showed that road characteristics, such as street width, played a large role in explaining the variance in traffic for wide streets, although configurational variables such as metric betweenness play a larger role in explaining the variance in traffic for narrow streets. They suggested that a theory of urban street hierarchy that could explain the difference between streets used to converge on an area and streets used as shortcuts between areas would be useful for understanding urban traffic flow. These two sorts of streets parallel Hillier's discussion of "linear" and "convex" flows (Hillier, 1999).

In "Atlanta: A Morphological History" (Haynie and Peponis, 2009), Haynie applies Doxiadis's assertion in Ekistics that urban centers are subject to continuous rebuilding and transformation. The authors study the historic progression of Atlanta's street network, within a radius around downtown, using directional and metric reach for analysis. They found that Atlanta initially lacked a highly integrated core. By 1928 the area south of downtown had high value for both metric and directional reach, but the neighborhood itself was low-density and residential. Eventually the interstate network cut through downtown and removed the remaining areas of highly integrated street networks. Thus, Atlanta never developed a street network that tied the center to the edge, because few of its important streets radiated from the center. Instead, its core network of highly integrated streets pass the center without penetrating it. Peponis and Haynie showed clearly that Atlanta's core shifted frequently as Atlanta grew. Despite this lack of a consistent center, we hope to show in our analysis below that, taken at a larger scale, Atlanta's pattern of centrality has a complex structure operating at multiple scales.

2.4 Synthesis

Urban centrality is a rich topic, and a better understanding of it will provide a deeper understanding of the function of cities. The analysis that follows is an attempt to apply the concepts of centrality discussed in this chapter to the actual form of of Atlanta to determine how empirical data about a modern city fits these models. We hope to discover whether Atlanta follows the infrastructural logic described by Doxiadis, with new growth occurring out of historic cores along new infrastructure, and whether centers in Atlanta form a linked network at multiple scales, as proposed by Alexander. We especially hope to examine Atlanta for signs of "pervasive centrality", Bill Hillier's indicator of a good city. Finally we hope to provide evidence disproving Koolhaas's cynical dismissal of Atlanta as disurban.

The analysis that follows contains several exploratory methods, each intended to describe and visualize the pattern of centers of Atlanta in the hope that a better understanding of the complexity beneath the surface of the city will allow us to better know its true nature. Our final analysis will attempt to show quantitatively how the structure of road networks draws commercial activity to different locations.

CHAPTER III

METHODOLOGY

It is clear from the literature reviewed that a deeper understanding of centrality would be valuable for planners, architects, economists, geographers, and all interested in the structure of urban space. Yet, extensive studies of centrality within individual cities are relatively few. One reason for the historically small number of studies is the difficulty of obtaining large datasets describing the distribution of features and activity within a city on a fine scale. Thankfully, an extensive dataset of land use in Atlanta was developed at Georgia Tech, allowing us to examine the distribution of centrality in great detail. This chapter will first describe our study area and the SMARTRAQ dataset. We will then describe the agglomeration of individual data points into discrete centers. Finally, we will describe directional and metric reach, two space syntax metrics we will use to measure urban form.

3.1 Study Area

In order to properly study the whole of Atlanta, our study area includes the ten county region used by the Atlanta Regional Commission, a regional planning agency created by the State of Georgia. As shown in Figure 4, the region includes the central counties of Fulton and Dekalb, the northwestern counties of Paulding, Douglas, Cobb, and Cherokee, the northeastern counties of Forsyth and Gwinnett, and the southeastern counties of Clayton, Henry, and Rockdale, and the southwestern counties of Fayette and Coweta. While not covering as large of an area as the twenty-eight counties used by the US Census Bureau to define the Atlanta-Sandy Springs-Marietta Metropolitan Statistical Area, these counties cover the majority of urban land in Atlanta. Our study area is large, but no larger than it needs to be to reach the urban fringe.

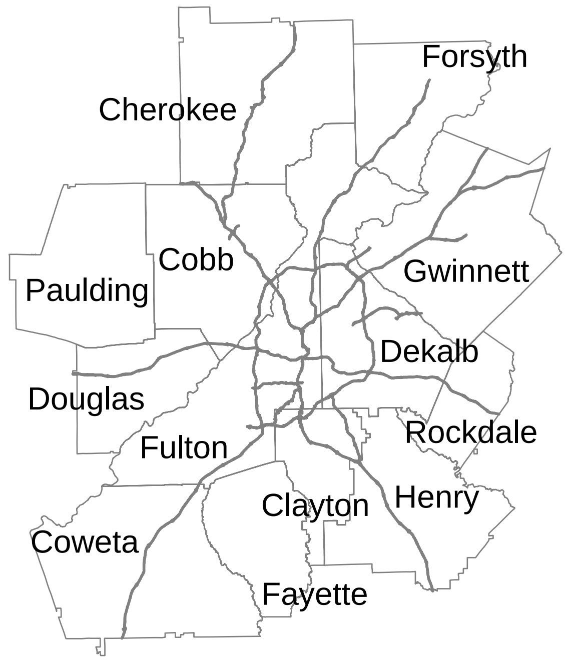

Figure 4: The study area includes the thirteen counties of metropolitan Atlanta, as defined by the Atlanta Regional Commission.

3.2 SMARTRAQ Data Source

Our primary data source is the SMARTRAQ database, produced by the Center for GIS at Georgia Tech in 2003. It contains parcel-level land use data for the 13-county metropolitan Atlanta area. Where data was unavailable at the scale of individual parcels, a larger scale land-use dataset was used. Both types of data were converted to centroids, and merged into a metropolitan-wide dataset of points. For each data point in the "office", "commercial", and "industrial" categories, a field indicates building square footage. If actual square footage was unavailable from the original data source, a regression analysis was used by the datasets authors to estimate square footage from each property's assessed value. This process was performed in the creation of the original dataset by the Center for GIS.

As discussed in the SMARTRAQ Land Use Database Documentation (SMA, 2003), nine of the thirteen counties were missing square footage values for more than

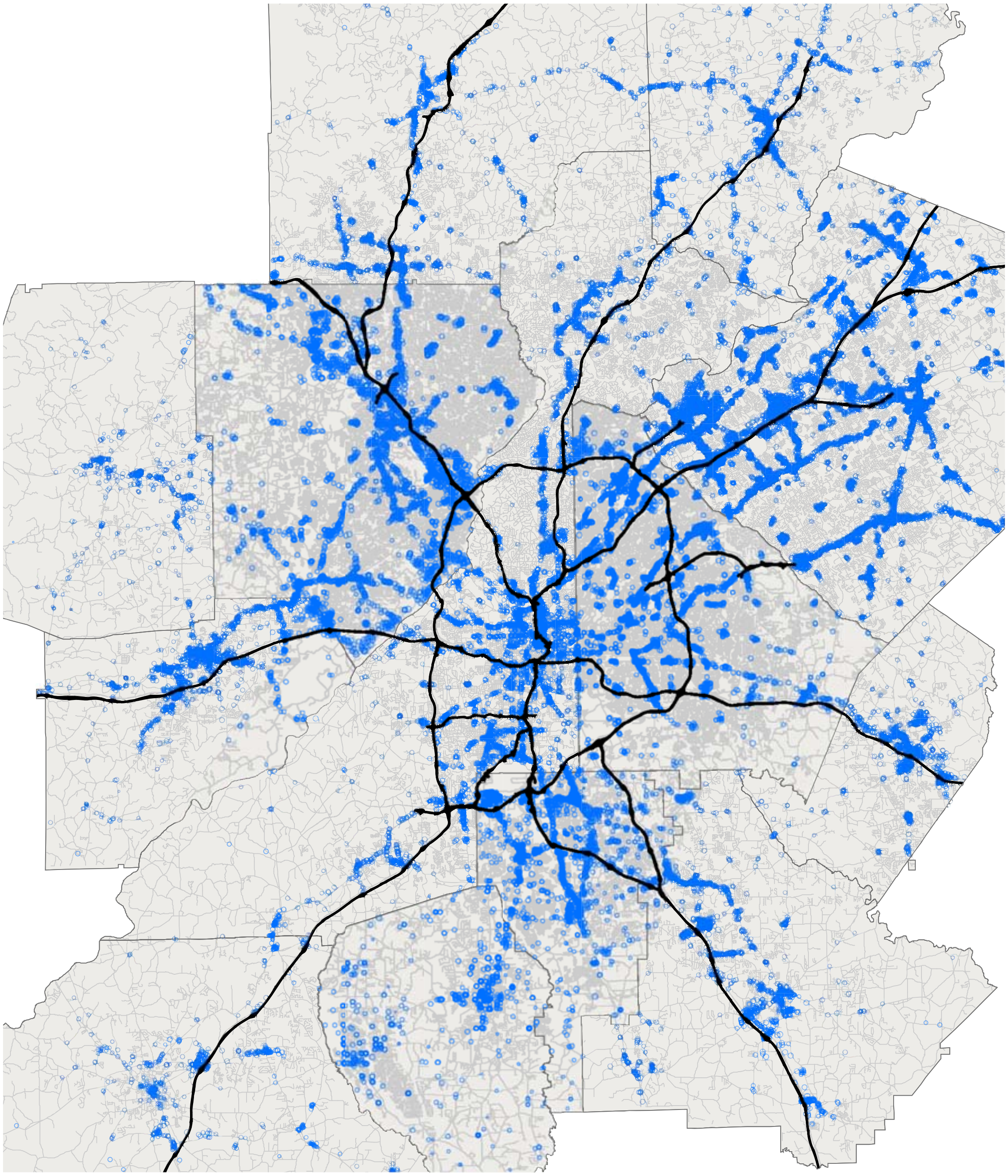

Figure 5: Each item with a commercial or office land use from the SMARTRAQ dataset is shown in blue.

fifty percent of the locations with commercial or office land uses. Because so many values were calculated from a simple regression estimation, this dataset is not necessarily accurate to specific locations. However, because it is consistently calculated, we assume errors are distributed consistently.

For our analysis we use the set of all data points in the SMARTRAQ database containing commercial or office land uses. Our use of commercial and office land uses is a proxy for the measure of activity intensity. Most urban land uses contain intense levels of activity at certain times. Sports stadiums host enormous crowds during events, but remain empty more of the time. Religious buildings draw many people on Saturdays and Sundays but few during the week. However, commercial and office land uses have high levels of activity on a routine basis, and they best reflect the sort of live centrality described by Hillier, so they were chosen for this analysis.

We included office land uses because the location of retail land uses varies greatly in American cities depending on a number of extraneous factors, such as land use regulation. Downtown Atlanta, for example, has an intense density of office space but relatively little retail activity. Still, it is clear that Downtown Atlanta is the sort of center Hillier intended when he described a "network of linked centers at all scales." (Hillier et al., 2008) Thus we chose to include office land uses in our analysis, assuming that they represented this centrality well in Atlanta.

The road network used for analysis came with the SMARTRAQ database. This data was originally compiled by the Georgia Department of Transportation and includes road centerlines for all state and local roads.

3.2.1 Data Correction

A cursory analysis of the square footage data reveals a number of anomalies. For example, the largest single square footage for any commercial or office data point is at the Atlanta Motor Speedway; however, the speedway is not actually a commercial land use but a recreational land use under the schema used by the SMARTRAQ dataset. Other very large data points are inaccurate as well. In Cobb County, five of the largest data points had an estimated square footage an average of roughly 200% larger than their current tax records indicated. Because of the size of the dataset, it is infeasible to correct all data points, so we chose to correct only the points with the largest estimated square footages. Fifteen data points had square footages larger than one million square feet and were estimated in the original dataset, so we verified the estimated square footages for these data points against current tax records (plus an additional data point in Cobb with an estimated square footage of 570,000 square feet that was adjacent to one of the other large data points). In Cobb, Henry, Dekalb, and Gwinnett Counties, each large data point was estimated to be roughly twice as large as it was in reality, though the deviation was not consistent. In Clayton County, one large data point was estimated accurately. In Fulton County, however, the four data points with large estimated square footages were each underestimated, in one case by half.

In addition to correcting the square footage estimation of very large data points, we also systematically removed a number of data points with duplicate values. For data points in the same vicinity (with a mean and standard deviation of less than 1000 meters in both east/west and north/south directions), with identical square footage values, identical land use values, identical parcel identifiers and year built values (which were often missing), we combined the data points into a single data point, with using the average east/west and north/south position for its location.

To prepare the roads dataset, we categorized each road as "non-freeway" or "freeway." The set of freeway roads included all limited access highways and their on-ramps, including the interstates, Georgia Highway 400, a portion of Peachtree Industrial Boulevard, University Parkway in Gwinnett County, Stone Mountain Freeway, and several smaller limited access roads. All other roads were classified as non-freeway roads. In the course of categorizing these roads, we found several gaps and misaligned road segments, typically at county lines, where continuous roads were not connected. We corrected these where we found them, but we did not systematically search the database for gaps.

3.3 Measuring Centrality

3.3.1 Kernel Density Analysis

After preparing and cleaning the data for both commercial and office land uses, we needed a method for estimating the intensity of commercial activity over space. Kernel density estimation (KDE) is a statistical method for spatial smoothing by estimating a density function from a set of discrete points. For each individual observation, a kernel function (such as the normal curve) is estimated. These kernel functions are summed for the set of all observations, producing a smoothed curve representing the density of the observed variable over space. A bandwidth r is specified for the kernel functions such that the kernel function reaches zero r units away from the observation. The use of kernel density estimation for our set of commercial land use data points is described in figures 6, 7, and 8.

Porta et al. (2009) describes kernel density estimation mathematically. The kernel density, $f(x)$ at a given point x is the sum of the surrounding kernel functions, $K(x)$, for n points within a bandwidth h:

$$f(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{1}$$

Porta cites Silverman (1986, p. 76) for the kernel function used by ArcGIS:

$$K(y) = \begin{cases} (3\pi)^{-1}(1-y^2)^2, & \text{if } y^2 < 1 \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

Thus the individual kernel functions for each point contribute nothing to the kernel density estimation for points further than the bandwidth distant.

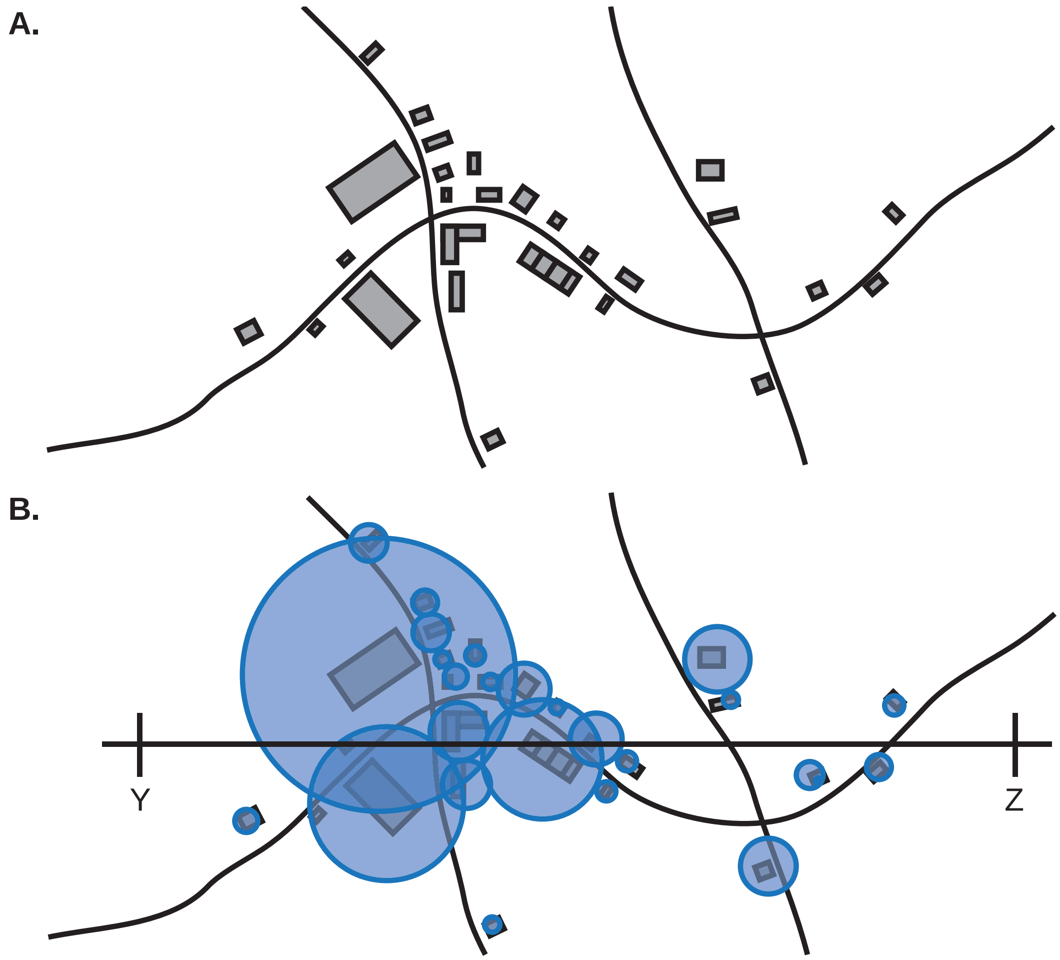

Figure 6: The process for deriving the set of centers from the SMARTRAQ data is described here and in figures 7 and 8. Consider a small commercial district, with commercial buildings shown in gray in (A) above. In (B) each building is represented by a point, with a magnitude determined by the square footage of the building, as in the SMARTRAQ data.

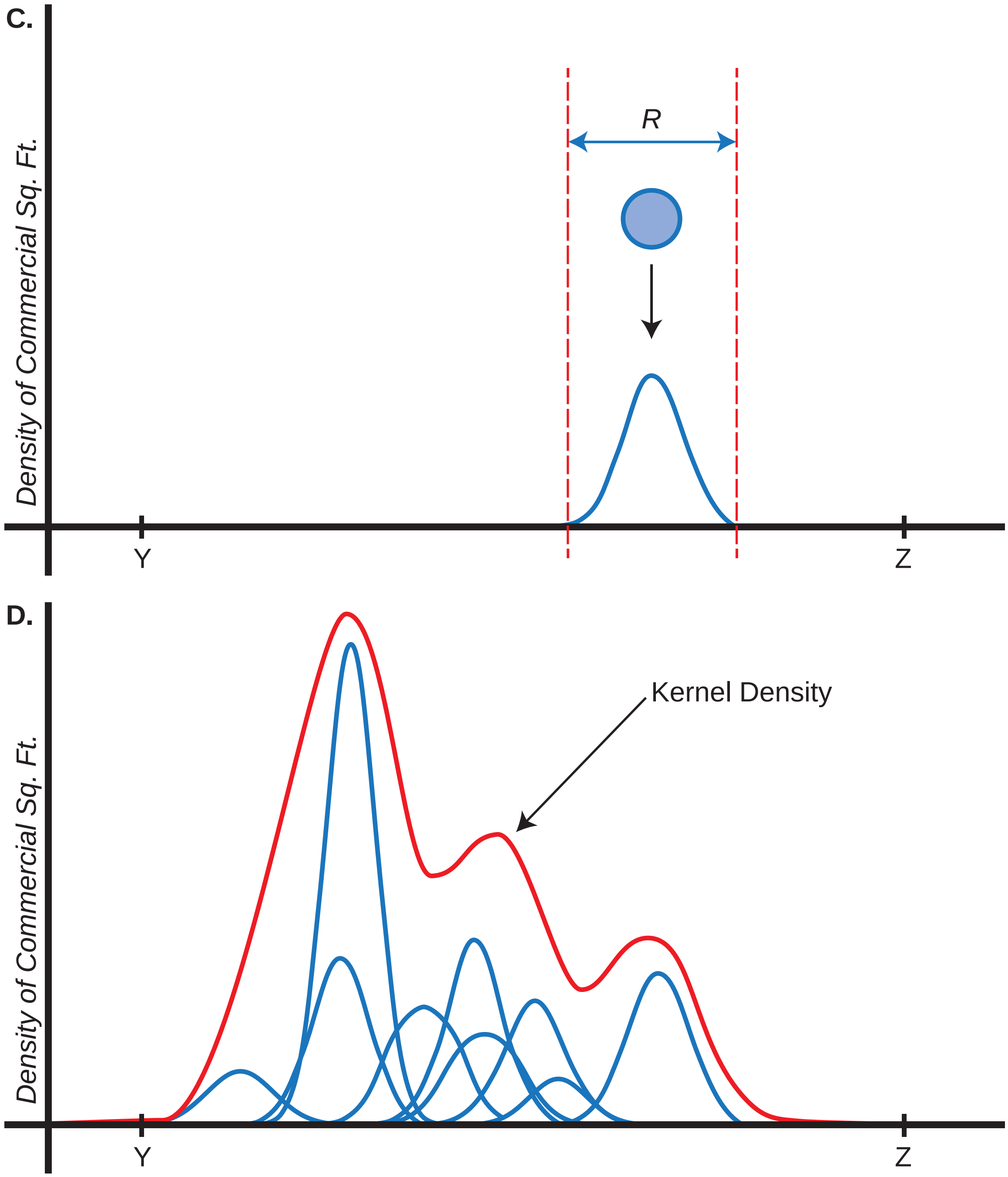

Figure 7: The kernel density estimation calculation applies a kernel function to each data point, as shown in (C). Each kernel function is scaled so that its peak value equals the magnitude of the data point. Then all of the kernel functions are summed to form the kernel density estimation, as shown in (D).

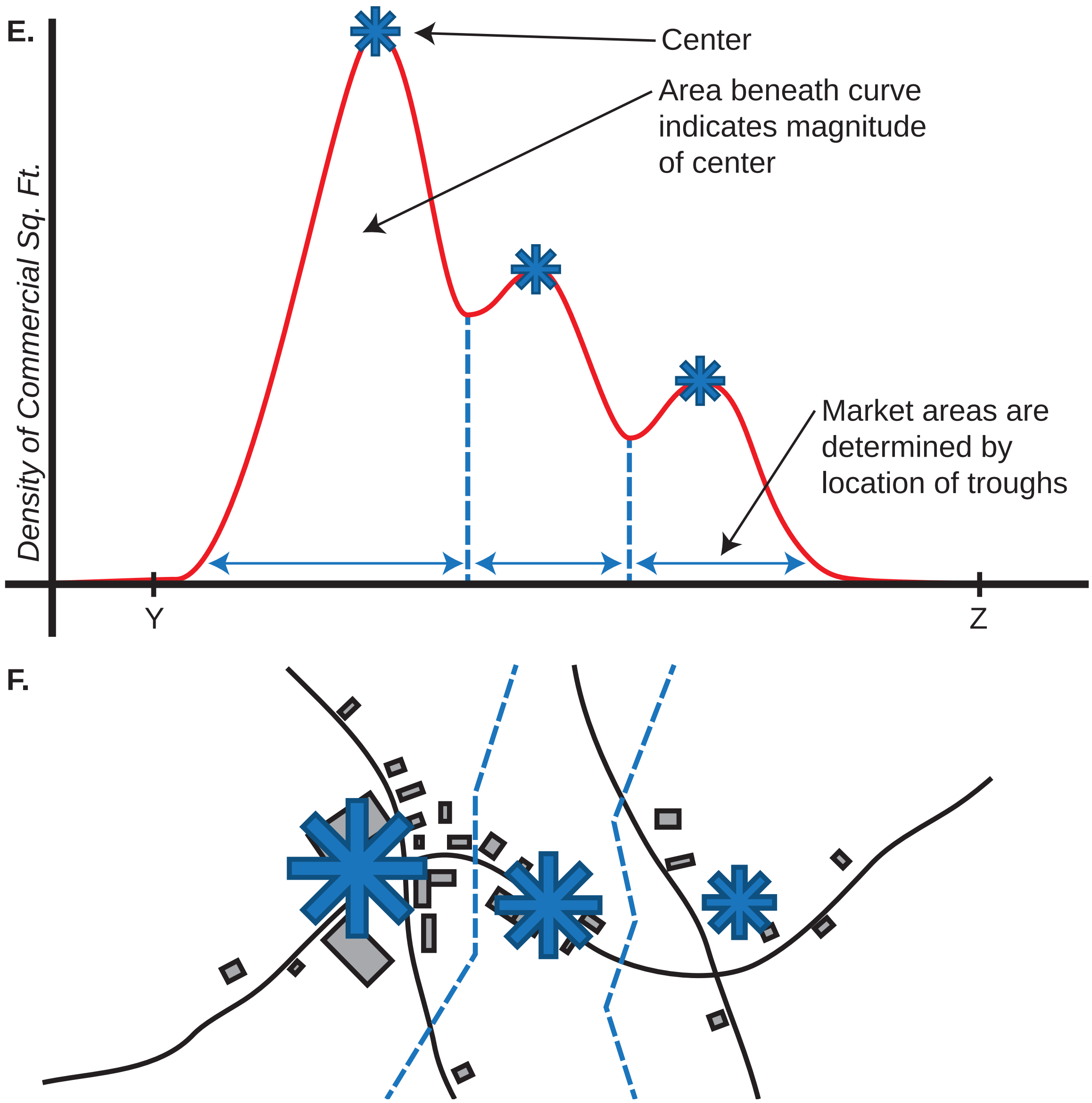

Figure 8: After the kernel density estimation is produced, each local maxima is determined to produce the set of all centers, as shown in (E). The kernel density function is then split into market areas corresponding to each center along the lines of local minima between centers. The magnitude of each center is determined by both the value of the kernel density function at that center and by the volume beneath the kernel density surface within that center's market area. (F) illustrates the application of these measures to the original set of data, with centers indicated by stars and market areas shown denoted by the dashed, blue lines.

Kernel Density Estimation is widely used in spatial statistics, including in similar analyses to our own. Porta used it for his analysis of commercial space in Bologna. Furthermore, commercial GIS packages, such as ArcGIS, include tools for calculating KDE, producing a grid of results stored as a raster data file. We found KDE a particularly useful method for estimating the distribution of commercial intensity because of several characteristics of the resulting raster. First, commercial space is distributed from disconnected data points into space, joining isolated data points into a shared measure. Second, the raster produced by KDE resembles an elevation raster. This both provides us with a convenient metaphor for the distribution of commercial intensity and allows us to use the numerous tools provided by GIS packages for analyzing elevation rasters. Third, the bandwidth variable can be changed to produce different amounts of smoothing in the resulting raster. These modifications produce anything from a surface of many small, sharp peaks, to a one easily sloped hill in the resulting raster. These various results allow us to measure the distribution of commercial space through different levels of attraction, from a large city-wide level of attraction, down to a very small, pedestrian scale level of attraction. Thus we are able to visualize and analyze commercial space at many scales.

For all raster analyses, we used a cell size of 150 meters (492.1 feet). Since our individual data points were calculated from the centroids of individual parcels, it would be impossible to determine the location of commercial activity with complete accuracy. The 150 m cell size provides a balanced combination of accuracy and a reasonably sized dataset for computing purposes, given the level of error inherent in our data.

We performed the kernel density estimation eight times using a geometric series of bandwidths: 0.125 miles (0.2 km), 0.25 miles (0.4 km), 0.50 miles (0.8 km), 1.0 mile (1.6 km), 2.0 miles (3.2 km), 4.0 miles (6.4 km), 8.0 miles (12.9 km), 16.0 miles (25.7 km). We began with 0.125 miles, because it is the smallest bandwidth within the series larger than the cell size, and we end with 16.0 miles, because the resulting KDE raster produces only one very large center in the process described below. Since each bandwidth is twice as large as the previous bandwidth, we can be certain that any level of intensity measured is substantially different from the previous measurement. Several of these measures correspond to standard travel distances in urban design studies. For example, O'Sullivan and Morrall (1996) studied the distances pedestrians walked to light rail stations in Calgary, Alberta and found that the mean walking distance was 422 meters (0.26 miles). In suburban areas pedestrians walked further, with a 75th-percentile distance of 840 meters (0.52 miles). Thus the 0.25 mile and 0.50 mile bandwidths correspond to the scale of commercial activity that could attract pedestrians from the immediate area and from the entire surrounding neighborhood respectively. Diagrams illustrating the kernel density rasters, represented as a three dimensional surface, are located in the appendix, in section C.1.

3.3.2 Generating a Set of Centers

After generating the KDE rasters of commercial activity for bandwidths from 0.125 miles to 16.0 miles, we analyze each to extract a set of centers represented as points. For each KDE raster, the set of centers at the respective bandwidth is equivalent to the set of local maxima on the KDE raster, where the magnitude of the KDE raster at that location is positive. In our topographic analogy, the set of centers is the set of peaks on the terrain. The raster analysis we used requires a minimum area over which a cell must be a local maxima. We chose to use a slightly larger than two cell (375 m) minimum radius, so that cells intersecting at a corner would not both be chosen as point centers. This method provides a minimum of eight surrounding cells over which a point center is the maximum value of the KDE raster. The results of this analysis are shown in Figure 9.

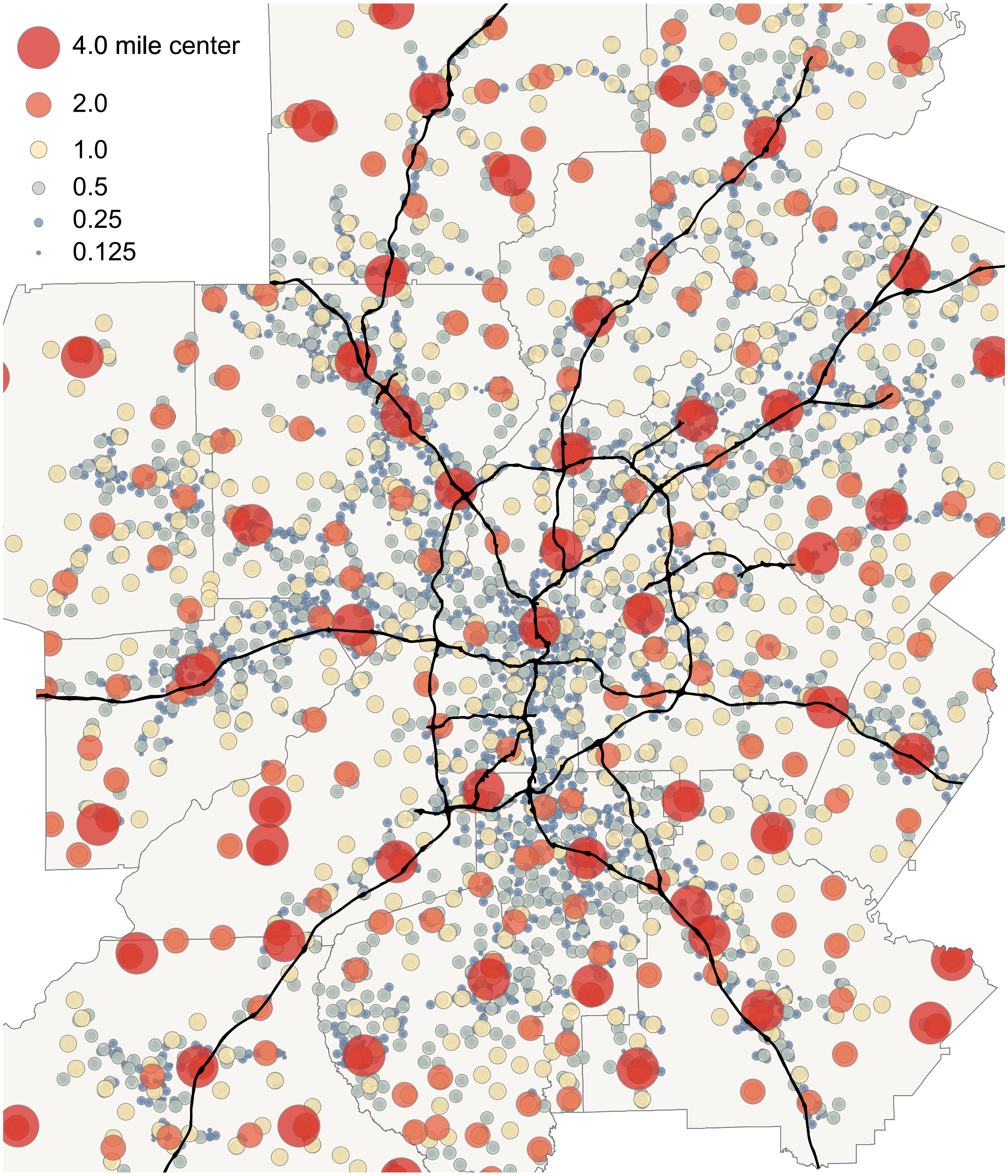

Figure 9: The kernel density estimation process generates a set of centers for each bandwidth. The smaller number of large-bandwidth centers are surrounded by a higher number of small-bandwidth centers. Additionally, larger bandwidths produce a pattern of centers more closely related to large-scale infrastructure than smaller bandwidths.

After generating the set of centers, we set out to delineate the polygons representing the spatial extent of each center. To distinguish these from the centers represented by points, these will be referred to as *market areas*. This set of market areas represents the area tied to each center, such that areas with a positive value on the commercial intensity surface (produced by kernel density estimation) are tied to the nearest point center along a path of increasing intensity. Put more simply, each market area is the hill tied to each peak, including surrounding areas with no commercial activity distributed to the nearest market area. Market areas were determined using ArcGIS's tools for delineating watersheds. By inverting the KDE raster and treating it like an elevation raster, ArcGIS could easily divide the raster into polygons representing watersheds. In this case the topographic metaphor explains the actual process used well. The set of market areas illustrates the pattern of commercial activity, but it is also necessary for calculating the dependent variables used in the analysis, as described below. Diagrams illustrating the set of market areas are in the appendix, in section C.2.

For each center, we calculated three dependent variables using different methods of measuring commercial intensity: the total estimated square footage ($EstSqFt\_Sum$), kernel density maximum (KD_Max), and kernel density volume (KD_Vol). Total estimated square footage is calculated by calculating the sum of the estimated square footage for each data point falling within a given market area. It represents the total square footage of commercial activity within each center, as estimated by the SMARTRAQ database. Kernel density maximum represents the maximum value of the kernel density estimation raster, that is, the value of the KDE raster at the point center. This relates to the maximum intensity of commercial activity; however, it tells us very little about the breadth of commercial activity. To understand both intensity and breadth of commercial activity, we measured kernel density volume, the volume of commercial intensity for each market area. This was measured by taking

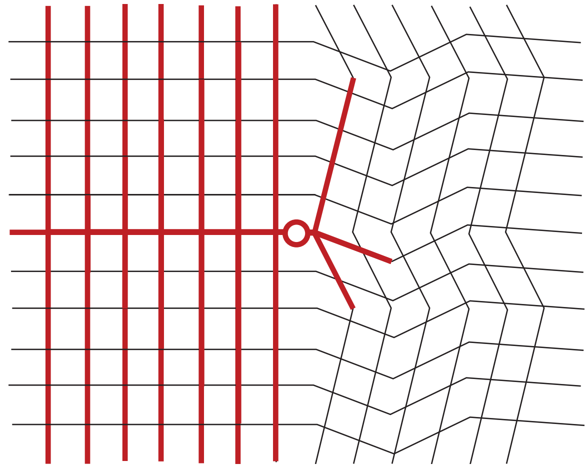

Figure 10: Directional reach with a radius of one turn for the road segment at the center is the length of the portion of road highlighted in red.

the sum of each cell's KDE value within each market area and multiplying by the area of each cell. This measure was used to provide an indication of both the level of intensity (that is, the "height" of the KDE surface) and the breadth of commercial activity (that is, the spatial area occupied) for each center. It is useful because, unlike the maximum value of the KDE raster, it increases for expansive centers that cover a large area, even if their maximum KDE value is small. Thus we have three dependent variables for use in our analysis.

3.4 Reach calculation

The independent variables in our analysis are measures of urban form calculated using Spatialist Lines, a software package developed at Georgia Tech. These measures, metric and directional reach, were originally described in Peponis et al. (2008). Directional reach is a measure of the amount of road centerline within a given number of direction changes from a road segment, as illustrated in Figure 10. Space syntax literature (such as Hillier and Iida (2005)) has shown that road segments that are accessible with fewer turns are more active, particularly in terms of pedestrian movement. Directional reach is similar to other measures used in space syntax, particularly

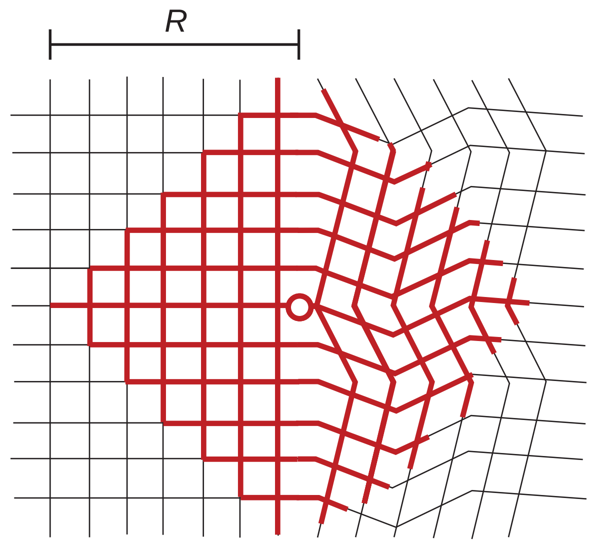

Figure 11: Metric reach with a radius of R for the road segment at the center is the length of the portion of road highlighted in red.

integration, which has been shown to correlate well with pedestrian movement. Metric reach is a measure of the amount of road centerline within a given path distance of a road segment, as illustrated in Figure 11. Both metric reach and directional reach are calculated using an angle threshold, a, a to accommodate the curvilinear nature of many streets. For any pair of road segments, the angle between the two is calculated. If the angle is less than or equal to $180 - a$ degrees, a move from one segment to the other is considered a turn.

Examination of previous reach calculations reveals that freeways distort reach values, because each is represented by multiple line segments. In order to limit this distortion, we calculated several reach measures on the set of all roads and several on the set of non-freeway roads. For non-freeway roads we calculated metric reach over a path distance of 0.25 miles (400 meters), 0.50 miles (800 m), and 1.00 miles (1.6 km) and directional reach given zero direction changes and two direction changes. For the set of all roads, we calculated metric reach over a path distance of 1.0 miles and 5.0 miles (8.0 km) and directional reach given zero direction changes and two direction changes. Thus we calculated nine total reach measures.

In order to compare the independent variables, the reach measures, to the dependent variables, the commercial intensity measures, we first clip each center's market area to the area of positive commercial intensity in the KDE raster, so that areas with zero commercial intensity have no effect on the reach values. We then use two methods for aggregating reach values within the market areas. For metric reach we calculate the mean reach value in each market area, weighted by the length of each road. This ensures that longer road segments are given the appropriate longer weight in the analysis, since reach is calculated independently of the length of each road segment.

Because directional reach is a configurational measure, it is therefore more likely to vary substantially within a small area. A major artery may have a substantially larger directional reach measure than a street intersecting it, particularly if the number of turns allowed is small. Because of this, taking a weighted mean of directional reach is completely inappropriate. A mean of metric reach values may give an excellent measure of network density in a center, but a mean of directional reach says quite little. In particular, the length of nearby noncommercial streets will substantially change the value of the mean. A commercial center located along a major artery with a cul-de-sac subdivision adjacent would have a substantially lower mean directional reach than the same center without the subdivision adjacent. Therefore, we can only seriously consider maximum values of directional reach for each center. These should provide a decent measure of urban form, in particular, for smaller centers. Thus we have nine independent variables for the analysis that follows below.

CHAPTER IV

ANALYSIS

Our methods produced a wealth of data, and we hope to use it to answer several questions about the distribution of commercial activity in the city. For example, we hope to discover why centers of different scales locate at different areas in the city, and what types of urban form attract different types of activity. This data allows us to explore Hillier's assertion that global processes decide where a center will form, while local processes guide the intensification of the center's grid (Hillier, 1999). Furthermore, we hope to discover why a given commercial center might locate on one road rather than another within the same neighborhood. So we will examine the distribution of commercial centers both throughout Atlanta and within individual neighborhoods.

We have previously described our methods for determining the location, extent, and qualities of centers at different scales. In order to analyze the data we created, we measured three quantities describing commercial activity and nine quantities describing urban form. The three quantities describing commercial activity are Total Estimated Square Footage ($EstSqFt\_Sum$), Kernel Density Maximum (KD_Max), and Kernel Density Volume (KD_Vol). Total Estimated Square Footage is calculated by calculating the sum of the estimated square footage for each data point falling within a given market area. It represents the total square footage of commercial activity within each center, as estimated by the SMARTRAQ database. Kernel Density Maximum represents the maximum value of the kernel density estimation raster, that is, the value of the KDE raster at the point center. This relates to the maximum intensity of commercial activity; however, it tells us very little about the breadth of commercial activity. To understand both intensity and breadth of commercial activity, we measured kernel density volume, the volume of commercial intensity for each market area. This was measured by taking the sum of each cell's KDE value within each market area and multiplying by the area of each cell. This measure was used to provide an indication of both the level of intensity (that is, the "height" of the KDE surface) and the breadth of commercial activity (that is, the spatial area occupied) for each center.

The quantities measuring urban form for each center were calculated as described previously. In all, nine reach measures were calculated, with five (two directional reach and three metric reach) calculated on the set of all non-freeway roads, and four (two directional reach and two metric reach) calculated on the set of all roads. This produced a total of nine measures of urban form. These are summarized, along with the measures of commercial intensity, in Table 1.

We will first examine the distribution of centers throughout metropolitan Atlanta, describing the pattern formed and highlighting those areas with a higher concentration of centers. We will then zoom in on two larger centers, describing their differences and discussing the general patterns formed by our data. We will then discuss the location of each center within its own market area, using a metric called the *reach percentile*. Finally, we will describe a series of regression analyses that attempted to describe how urban form generates centrality on a large scale in Atlanta.

4.1 Pattern of Centers

Our production of a system of centers and their corresponding market areas has presented us with a method for describing the pattern of urbanism present in Atlanta. These centers are distributed in an overlapping hierarchy of different scales as shown in Figure 9, such that it appears that some portions of Atlanta have very high numbers of centers, at many different scales, while others have only a small number of centers,

Table 1: Description of independent and dependent variables

Independent Variables: Urban Form Metrics	
DR0L_max	Directional Reach, 0 turns, on non-freeway roads, compiled by maximum value
DR0A_max	Directional Reach, 0 turns, on all roads, compiled by maximum value
DR2L_max	Directional Reach, 2 turns, on non-freeway roads, compiled by maximum value
DR2A_max	Directional Reach, 2 turns, on all roads, compiled by maximum value
MR025L_mean	Metric Reach, 0.25 mile radius, on non-freeway roads, compiled to a weighted mean
MR050L_mean	Metric Reach, 0.50 mile radius, on non-freeway roads, compiled to a weighted mean
MR100L_mean	Metric Reach, 1.0 mile radius, on non-freeway roads, compiled to a weighted mean
MR100A_mean	Metric Reach, 1.0 mile radius, on all roads, compiled to a weighted mean
MR500A_mean	Metric Reach, 5.0 mile radius, on all roads, compiled to a weighted mean
Dependent Variables: Measures of Commercial Intensity	
KD_Max	Maximum value of the KDE raster
KD_Vol	Volume of the KDE surface (the sum of the KDE raster multiplied by the area of a grid cell)
EstSqFt_Sum	Sum of the square footage for each commercial data point in the center

centers only at a few scales, or no centers at all. These patterns reflect the actual complexity of the urban structure in certain areas – it is impossible to fulfill Hillier's suggestion that in a good city you are always close to both large and small centers without a rich network of centers at multiple scales nearby. In order to illustrate the relative complexity of different portions of Atlanta, Figure 12 is a division of Atlanta into a two square mile grid. Each cell of the grid is colored by the number of centers within it, from zero to twenty.

These two diagrams illustrate the complex nature of centrality in Atlanta. Far from being disurban, Atlanta contains a complex, overlapping hierarchy of centers at many scales. The distribution of these centers follows large roads, with most 4.0 mile bandwidth centers located along freeways or on corridors intersecting the freeway network. Smaller bandwidth centers seem to follow a linear pattern in some areas, such as the northeastern suburbs, but they seem more well-distributed in other areas, such as Clayton County, to the south. However, in all areas except for the very low density areas on the periphery, the pattern of centers forms a pattern similar to that proposed by Central Place Theory. A smaller number of large-scale centers is surrounded by increasing numbers of smaller scale centers.

4.2 Examination of Focus Areas

We will now move to a smaller scale to examine the distribution of our centers, their market areas, and the measures of reach on the roads surrounding them. We will compare two major centers – the city of Decatur and the Perimeter Center area. Decatur is one of the oldest centers in metro Atlanta, founded in 1823. Perimeter Mall in Perimeter Center opened in 1971 and expanded in 2000. Comparing between these two areas should allow us to begin to form conclusions about the distribution of centers in Atlanta and about how urban form affects that distribution.

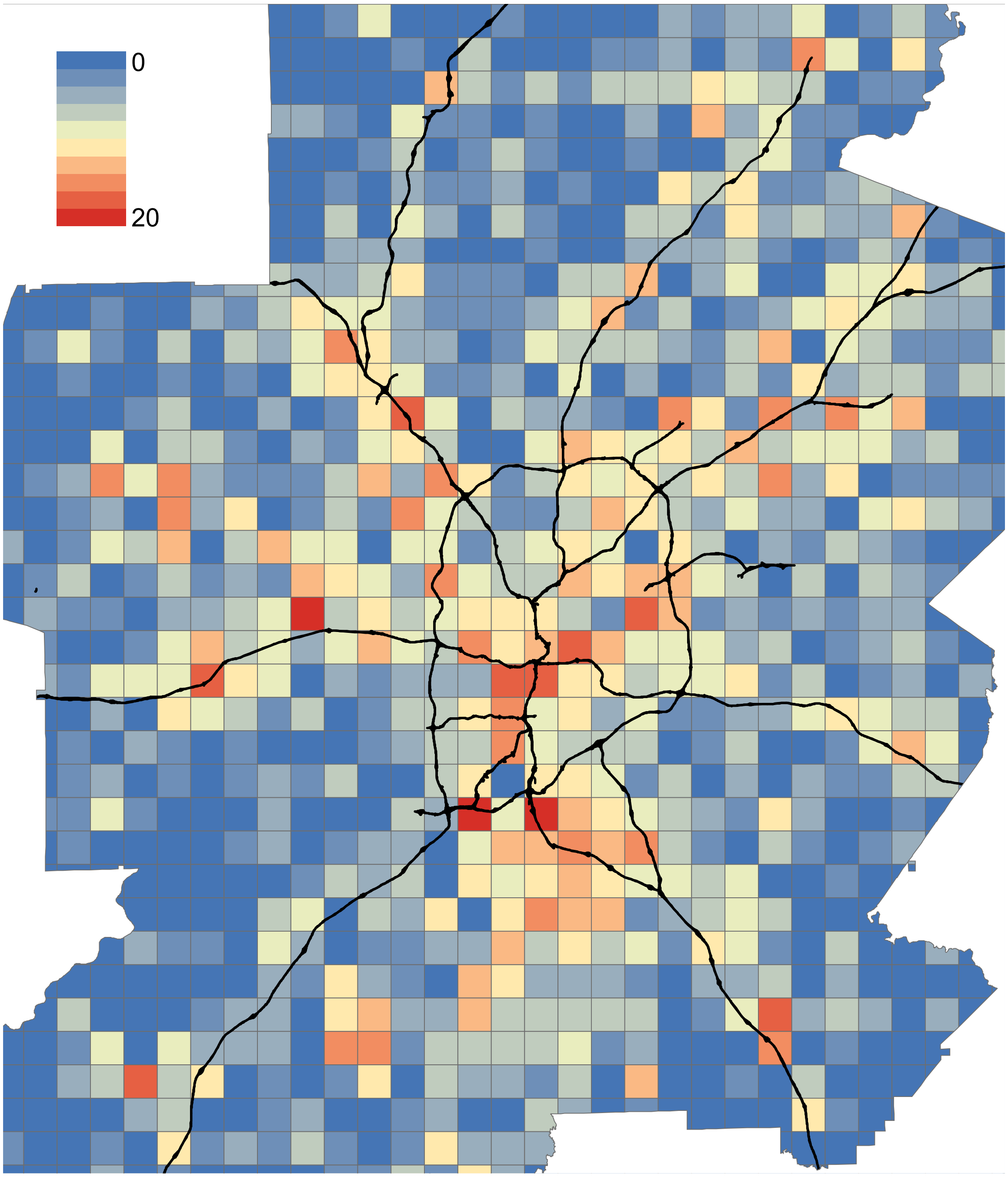

Figure 12: A two mile by two mile grid is laid on Atlanta, and the number of centers within each cell is summed. Generally speaking, the cells with the highest concentration of centers tend to fall along the freeway. Central Atlanta has a high number of cells with high concentration, but many concentrated cells fall in dense centers of activity in the periphery.

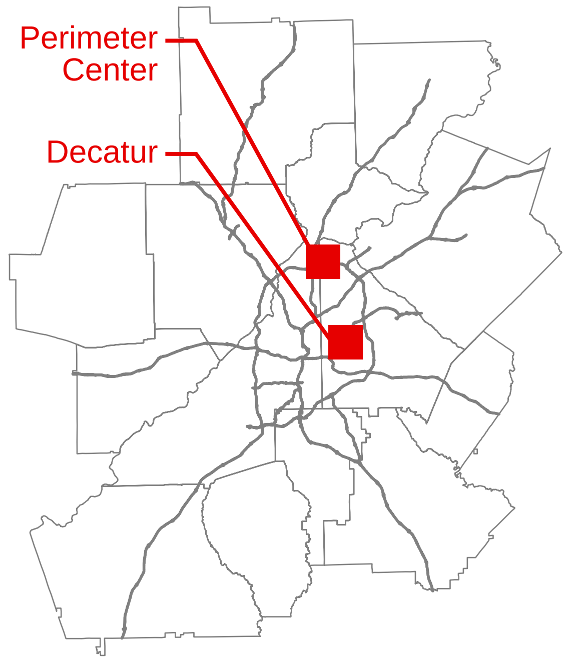

Figure 13: Decatur and Perimeter Center were chosen as focus areas for more detailed analysis.

4.2.1 The Pattern of Centers and Market Areas

A side-by-side comparison of each focus area, shown in figures 16 through 25 below, allows us to better understand the pattern of centers, as represented by their market areas, created by the process described in the previous chapter. Figures 14 and 15 serve as a reference for locations described below. The 0.25 mile and 0.50 mile bandwidths form very coherent patterns of centers in Decatur. Both bandwidths select obvious clusters, but each forms a distinct pattern. That is, the 0.25 mile bandwidth centers typically merge with their neighbors into larger centers with similar frontiers at the 0.50 mile bandwidth. Thus each of these forms a distinct scale of activity in Decatur. However, the smallest bandwidth that seems to form a distinct scale of activity in Perimeter Center is the 1.00 mile bandwidth. Thus it appears that Perimeter Center lacks the fine grained scale of activity found in Decatur, though both Decatur and Perimeter appear to have a large-scale level of commercial activity. Though it is difficult to determine how well the 2.0 through 8.0 mile bandwidths fit the patterns of activity from this small scale, larger scale maps indicate that, while the 2.0 and 4.0 mile bandwidths reflect an intuitive distribution of centers, the 8.0 mile bandwidth appears much more haphazard, with two large central centers, and multiple fringe centers. The largest bandwidth used, the 16.0 mile bandwidth, contains just one large center, encompassing all of the Atlanta Metropolitan Area.

Thus, a brief descriptive analysis based on intuition and visual patterns suggests that Atlanta contains commercial centers operating at six scales, represented here by the 16.0, 4.0, 2.0, 1.0, 0.50, and 0.25 mile bandwidths. Our comparison between Decatur and Perimeter Center suggests that some areas contain more levels of scales than others, and thus some areas of the city seem to have more complex patterns of commercial activity than others. However, to truly test this idea, we would require a method for determining the goodness of fit of our market areas to the actual distribution of commercial properties.

4.2.2 The Structure of the Road Network

Just as a side by side comparison of the pattern of centers for each bandwidth allowed us to better understand the distribution of commercial activity in Decatur and Perimeter at different scales, so a side by side comparison of each of the reach values, as shown in figures 26 through 43, allows us to better understand the differences in the structure of each area's road network.

Directional reach is strongest on long continuous roads, and, when the turn radius is greater than zero, on those roads connect to one or more long continuous roads. It is useful for highlighting the skeletal structure of an area's road network. Perimeter Center has many fewer well-integrated streets than Decatur, owing largely to its less dense, less well-connected road network. It follows that, other than large-scale developments such as Perimeter Mall where the street network is sparse, commercial properties cluster tightly to well-connected roads. Decatur's pattern is less clear, as it

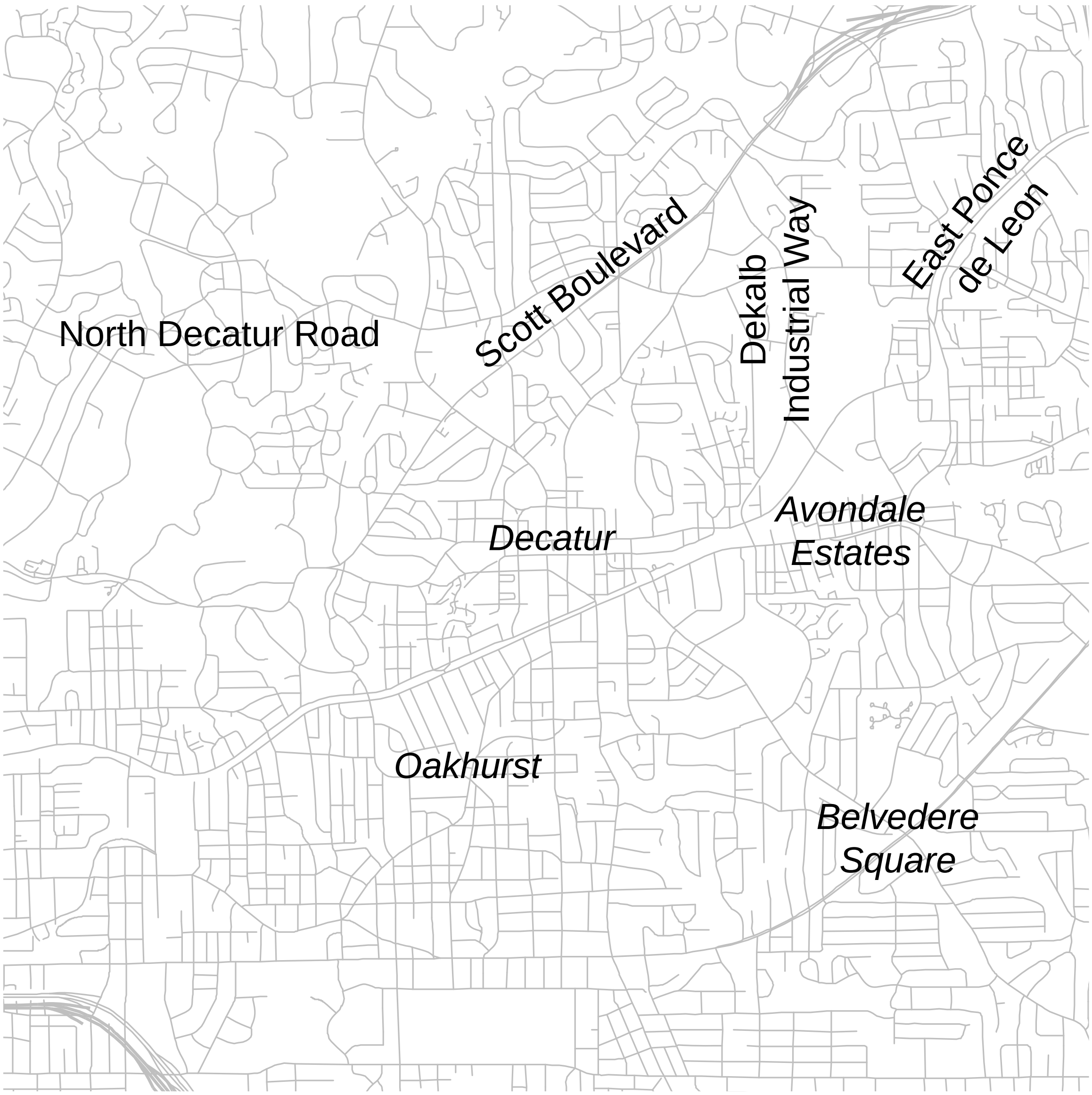

Figure 14: Key to locations in Decatur focus area

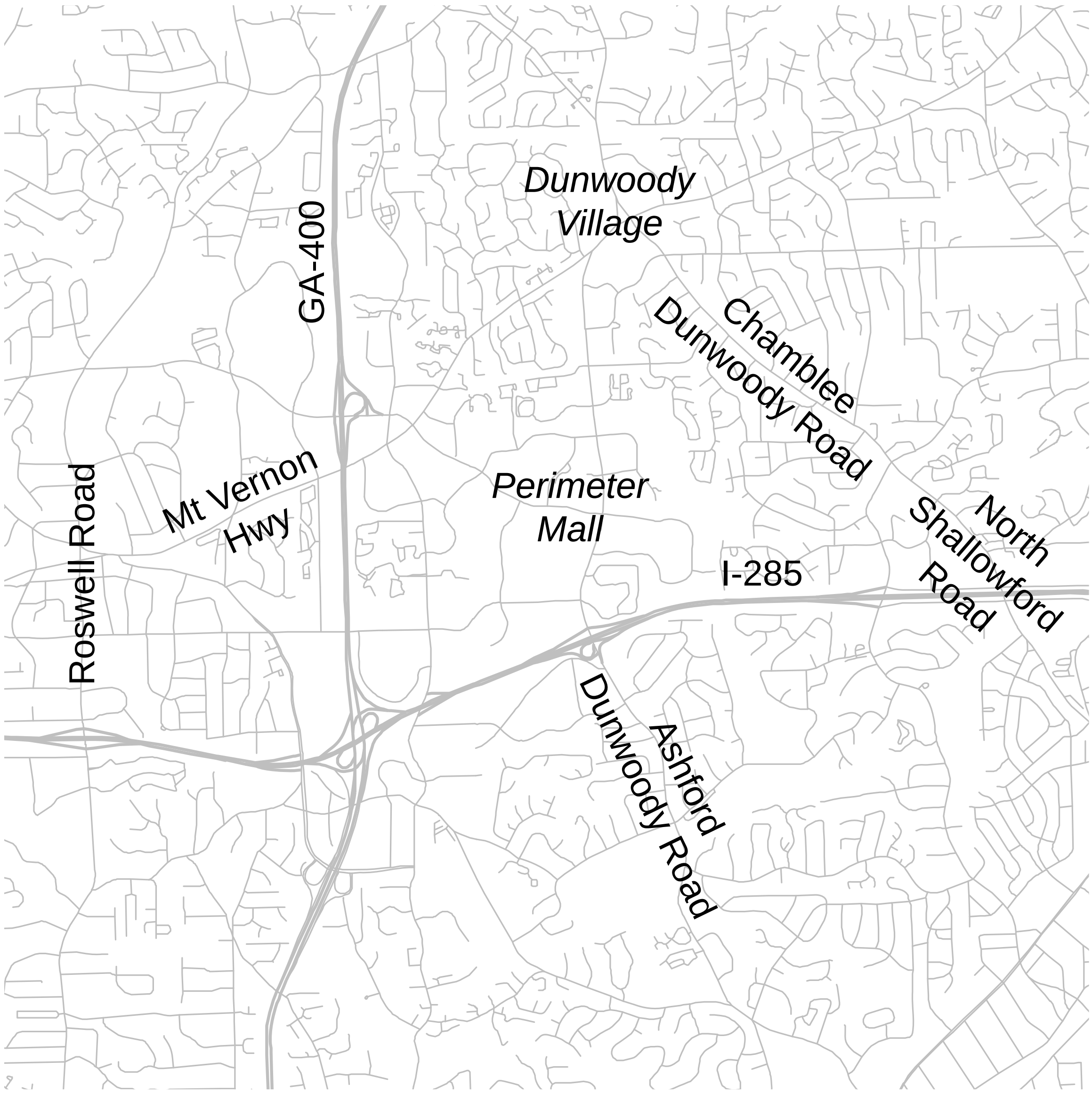

Figure 15: Key to locations in Perimeter Center focus area

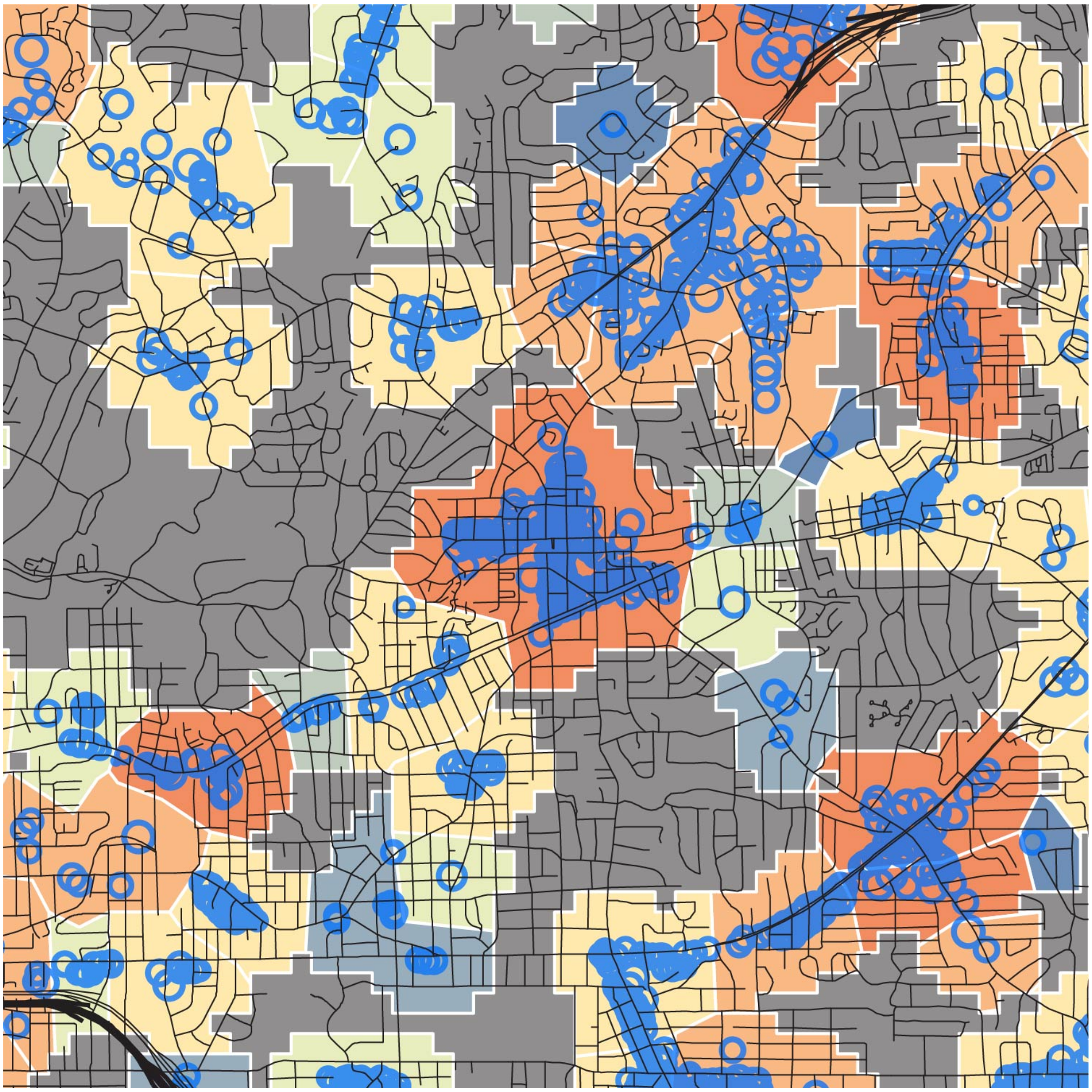

Figure 16: Decatur centers, 0.25 mile bandwidth

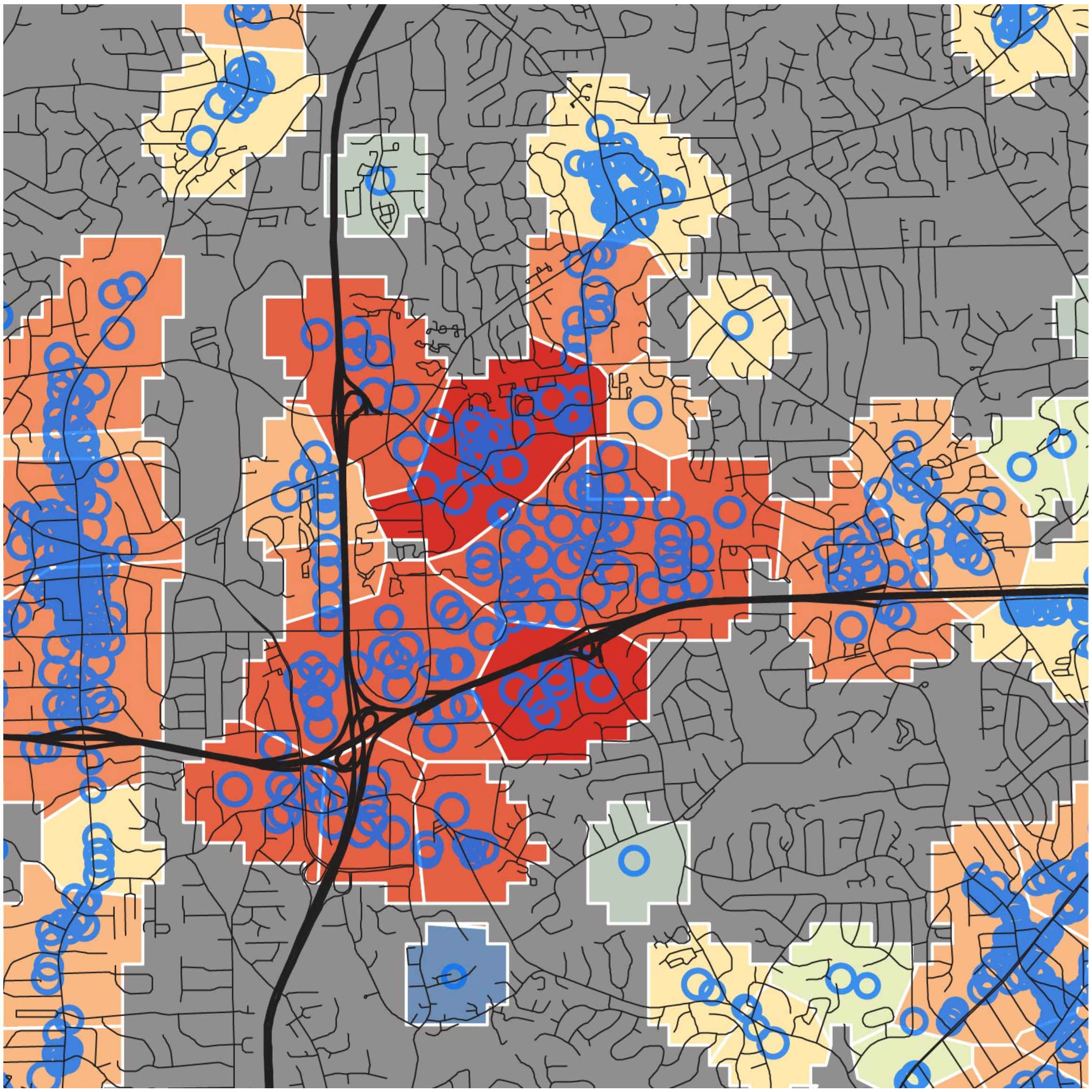

Figure 17: Perimeter Center centers, 0.25 mile bandwidth

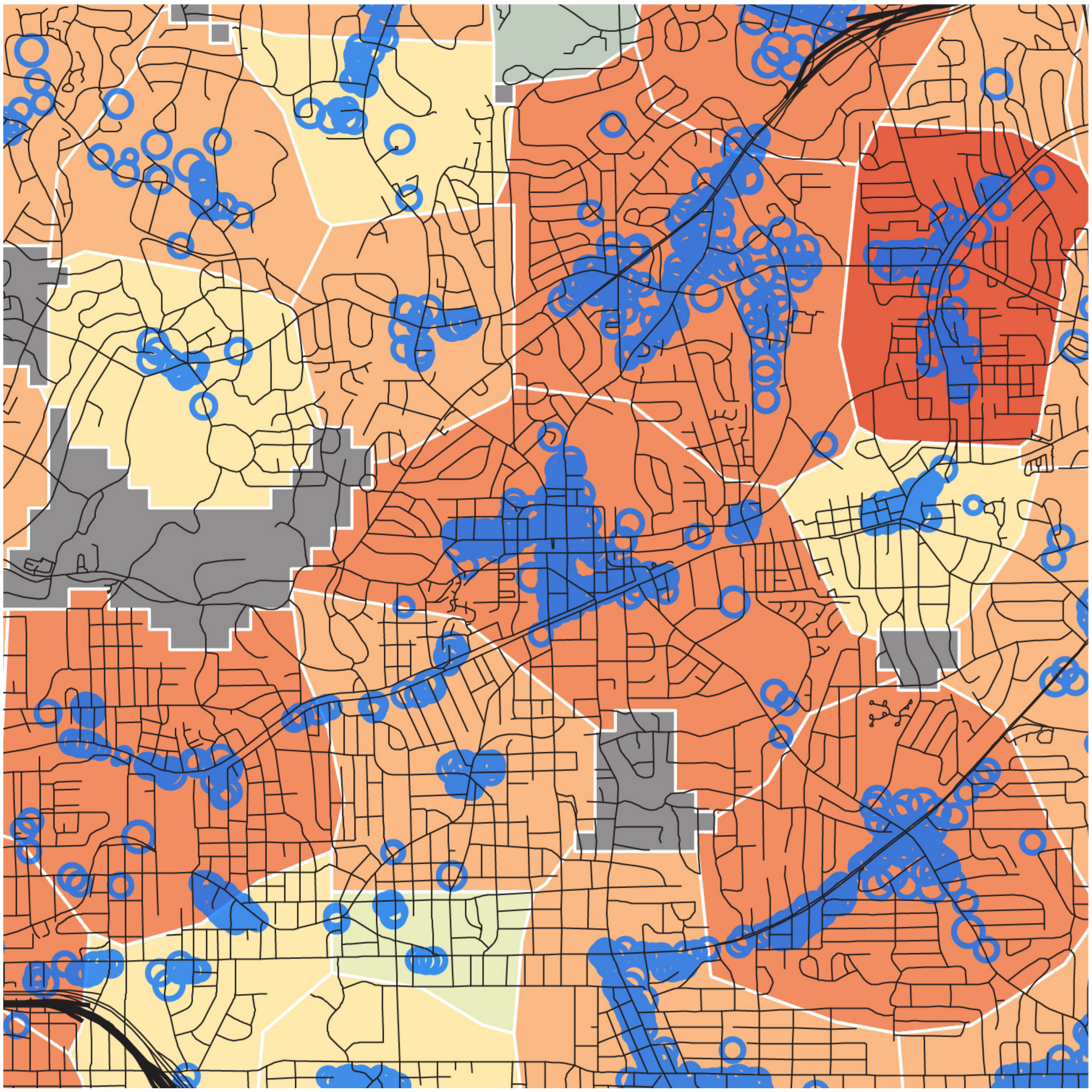

Figure 18: Decatur centers, 0.50 mile bandwidth

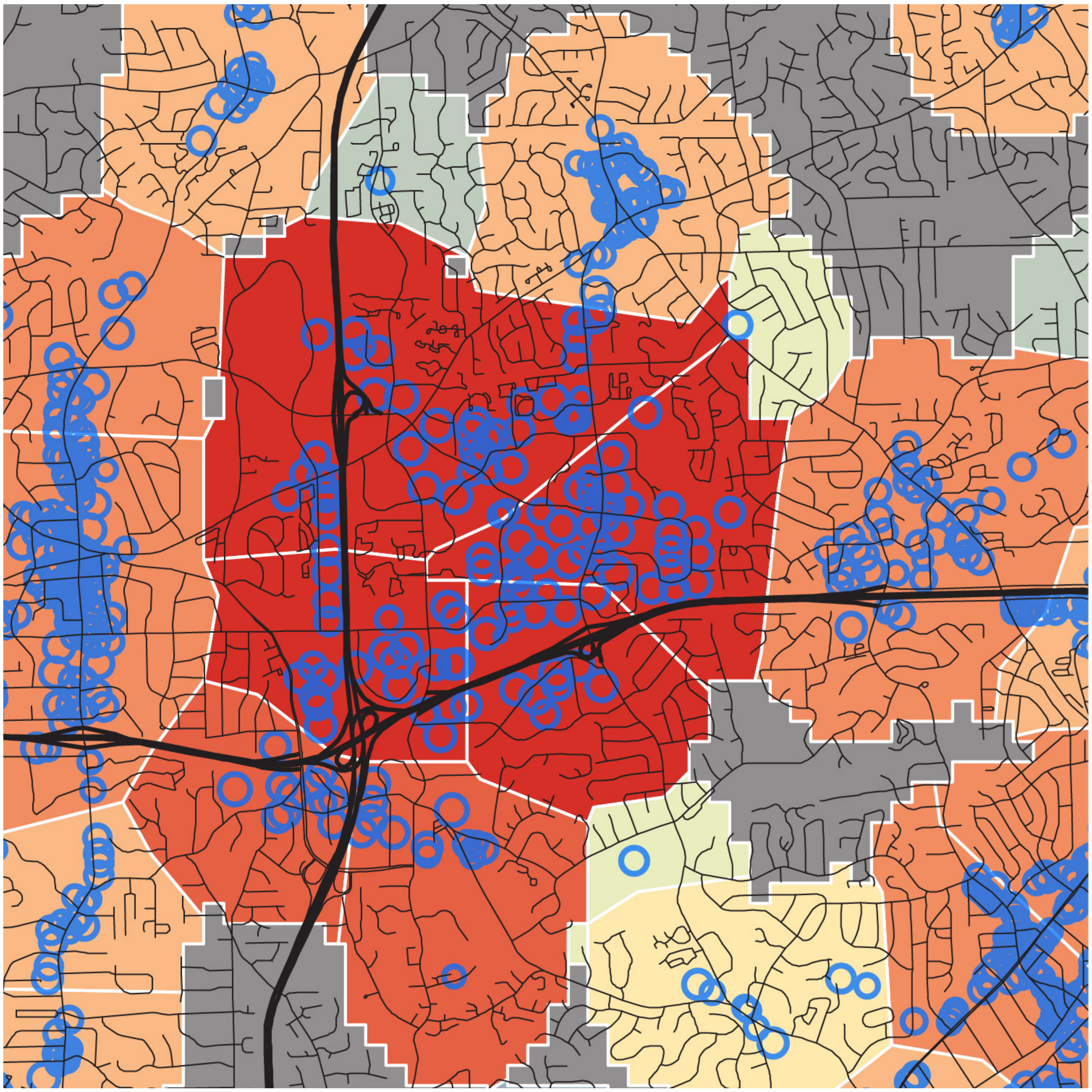

Figure 19: Perimeter Center centers, 0.50 mile bandwidth

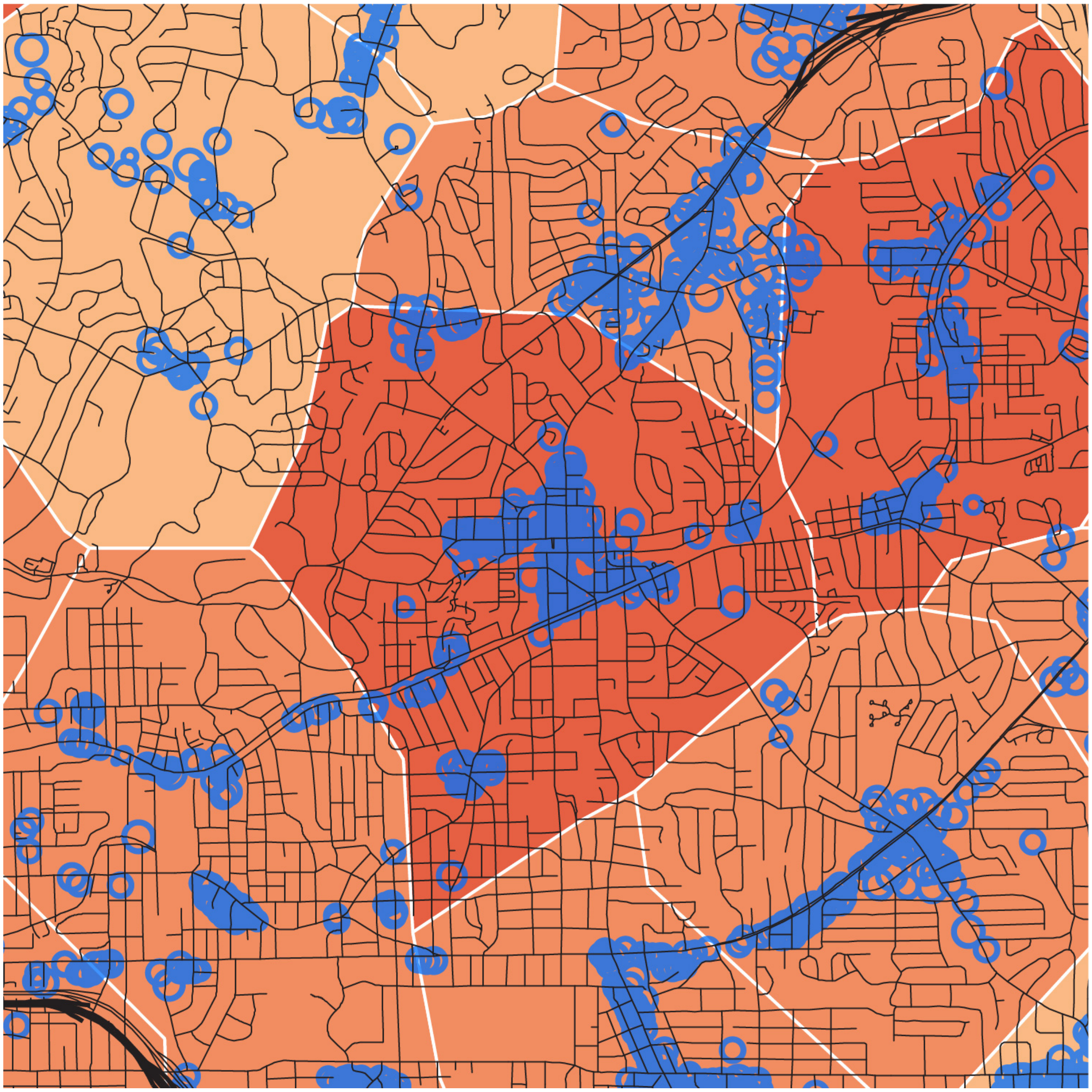

Figure 20: Decatur centers, 1.0 mile bandwidth

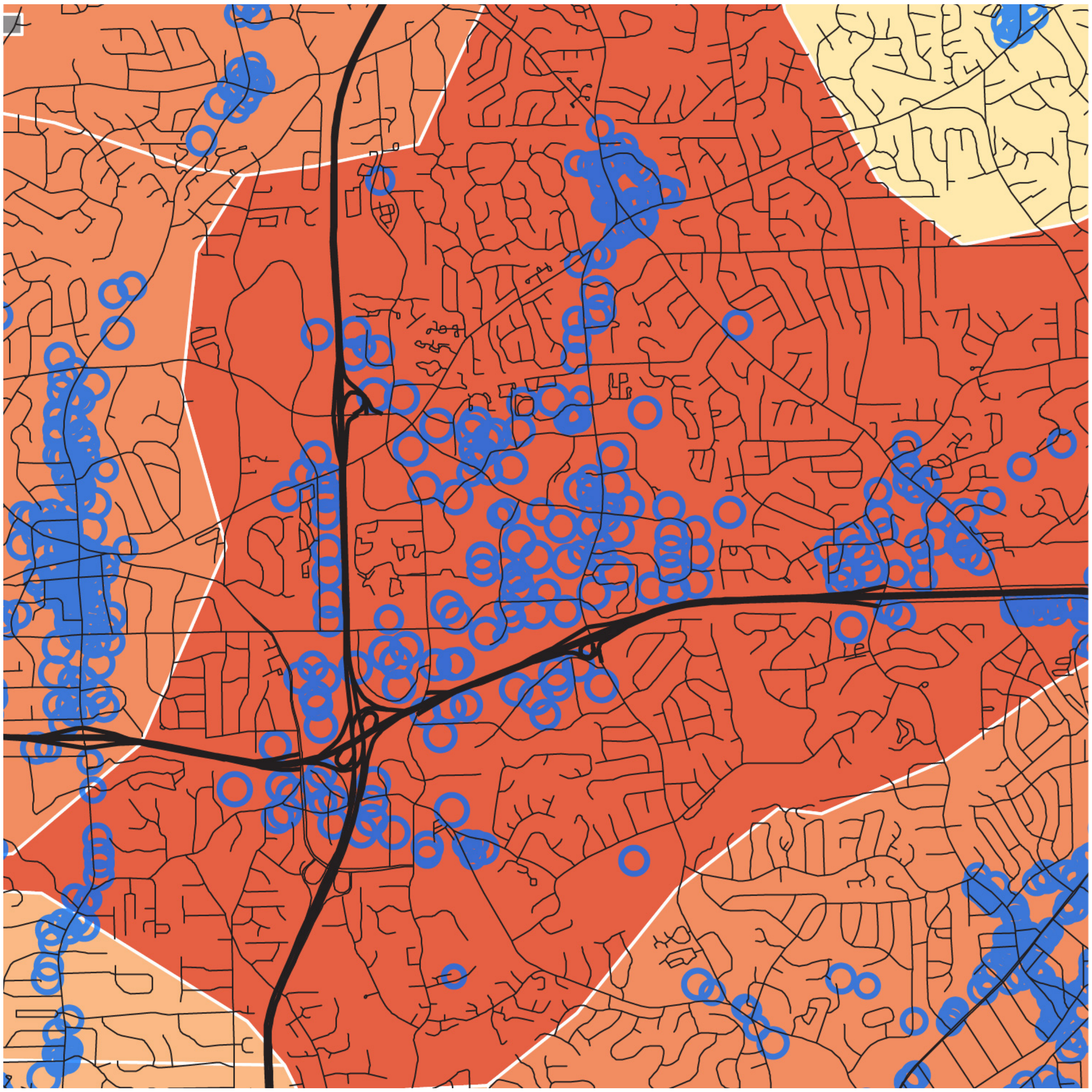

Figure 21: Perimeter Center centers, 1.0 mile bandwidth

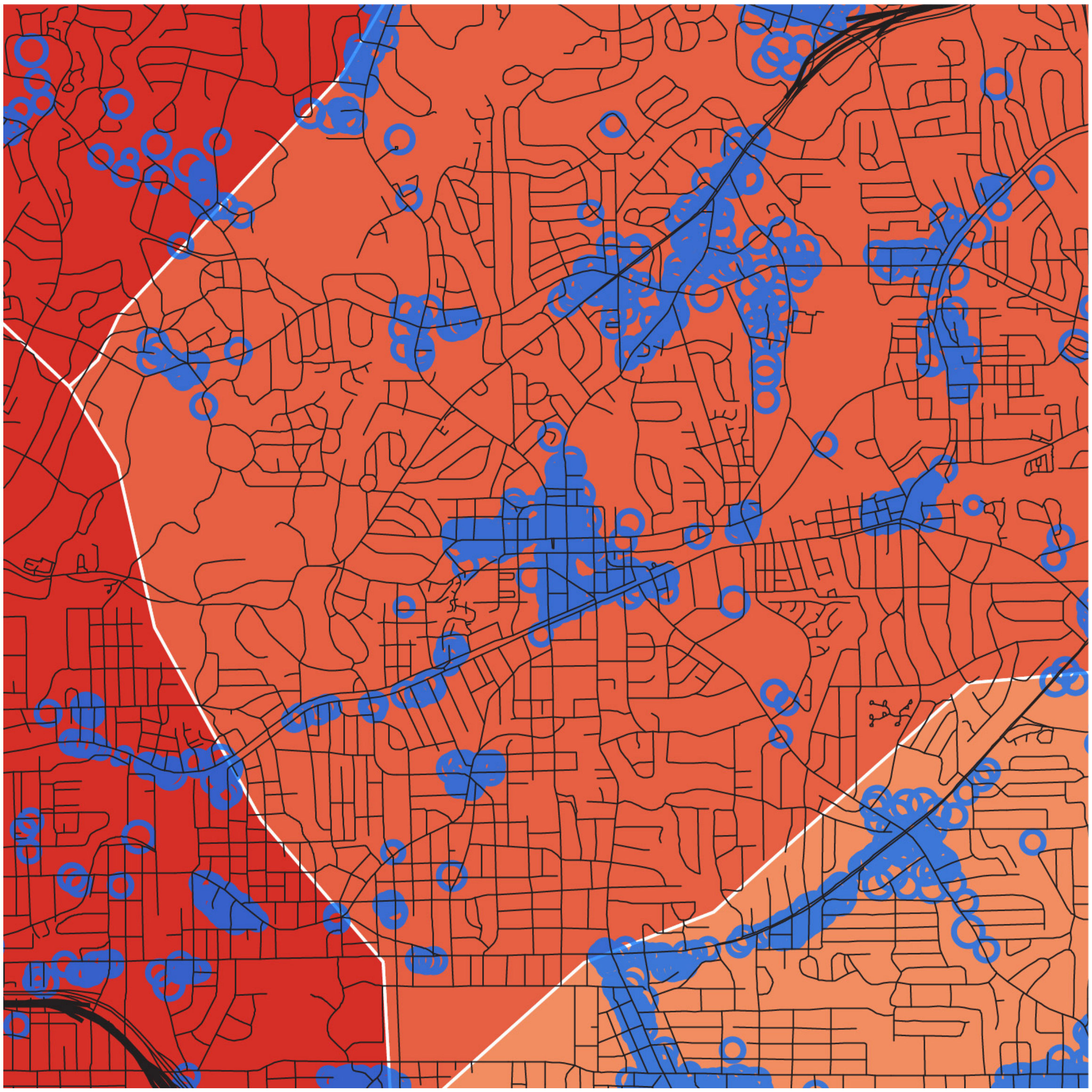

Figure 22: Decatur centers, 2.0 mile bandwidth

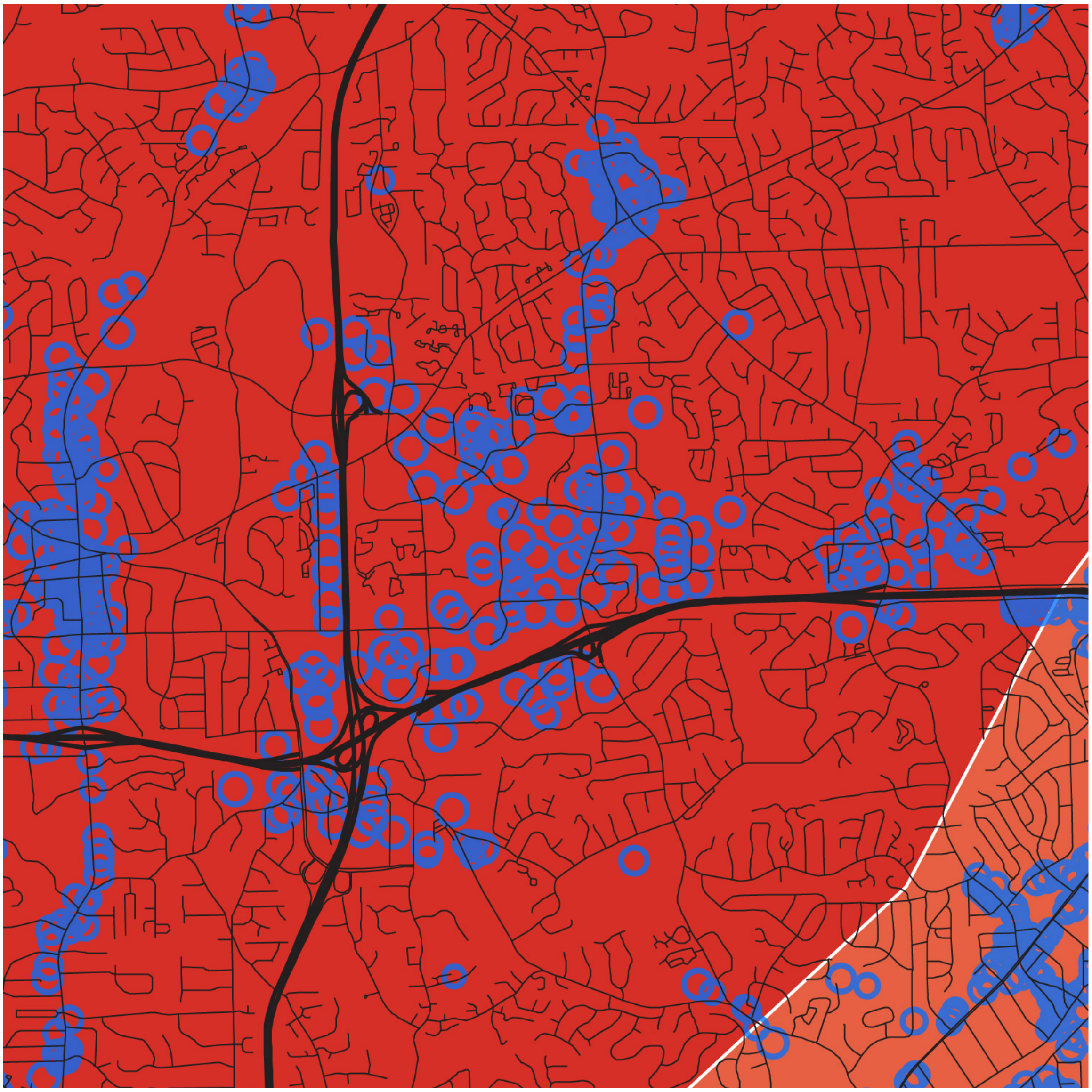

Figure 23: Perimeter Center centers, 2.0 mile bandwidth

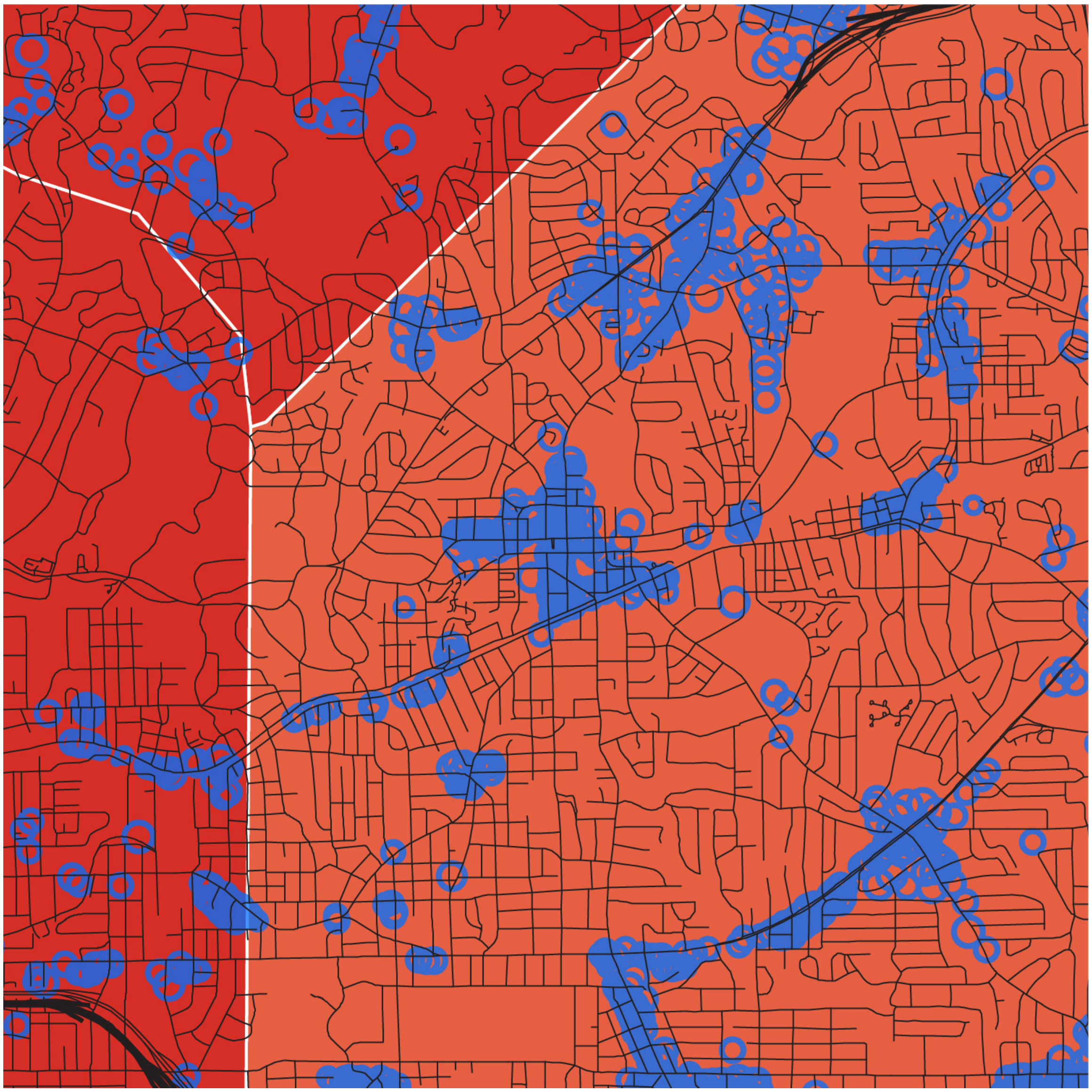

Figure 24: Decatur centers, 4.0 mile bandwidth

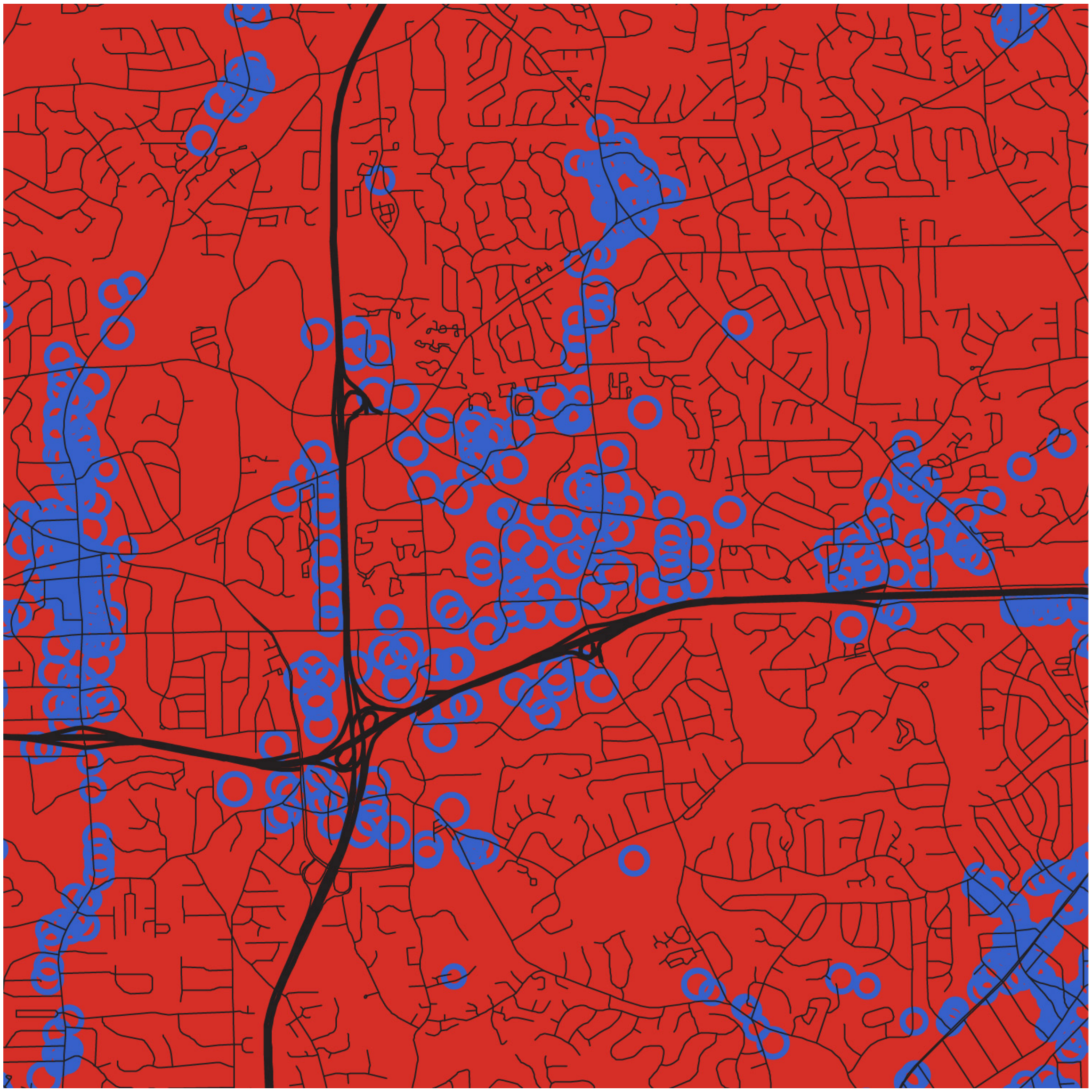

Figure 25: Perimeter Center centers, 4.0 mile bandwidth

is muddied by the high number of well-connected streets in the southwest portion of the map, where the grid-like neighborhood streets are far more well-connected than residential streets elsewhere in Decatur or Perimeter.

Metric reach is highest in areas of dense, well-connected street networks. As shown below, small-scale measures, such as a 0.25 mile radius, highlight a very immediate area of network intensity. This is particularly visible in several areas in Decatur, such as Downtown Decatur and the East Ponce De Leon corridor north of Avondale Estates, where high metric reach and the location of commercial activity is nearly identical. In general, as the radius of metric reach grows, metric reach highlights more and more streets, until 5.00 mile metric reach highlights nearly every road in both Decatur and Perimeter. At lower radii, especially the 0.25 mile radius, the difference between Decatur and Perimeter is striking. Whereas in Decatur commercial land uses tend toward higher metric reach values, in Perimeter the opposite is true. The areas highlighted by metric reach in Perimeter are most often residential neighborhoods while commercial activity both and large and small scale tends to locate in areas with sparse street networks.

An overall comparison of the location of commercial activity to reach values suggests three general patterns among areas with high commercial activity. First, some areas, such as Downtown Decatur and Avondale Estates, have both a high metric reach and a high directional reach. This pattern is common among older commercial centers and reflects a development process where well-connected roads attract development, resulting in further growth of the nascent center and additional intensification of the street network.

Second, other areas, such as the Belvedere Square area southeast of Decatur, the Dunwoody Village area north of Perimeter Mall, and the Roswell Road corridor, have clusters of commercial intensity along roads or intersections with high directional reach, but low metric reach. These areas have intense activity along a corridor or near an intersection, but they show few signs of network intensification. In some cases parking lots and access roads substitute for network intensification, allowing commercial activity to extend further from the corridor than otherwise possible.

Finally, other areas, such as the triangle formed by Chamblee Dunwoody Road, Shallowford Road, and I-285 east of Perimeter Mall and the area around Scott Boulevard, Dekalb Industrial Way, and North Decatur Road north of Decatur, are distinguished by clusters of commercial activity surrounded by roads with high values of directional reach. These areas show no outward signs of network intensification; in many cases parking lots and access roads have replaced the intensification of the actual road network, allowing commercial activity to fill entire superblocks. At a large scale, the Perimeter Mall area fits this pattern too. It is surrounded by four roads with high values of directional reach – I-285, Georgia 400, Ashford Dunwoody Road, and Mount Vernon Highway – and it is nearly completely filled with commercial land uses, often accessible by access roads, parking lots, and dead end roads. Thus in many ways the first pattern, the third pattern, and the Perimeter Mall area reflect the same pattern of development, though the third has a larger scale and higher level of infrastructure.

To summarize, in Perimeter Center, commercial property clusters around roads with high directional reach and shows little correlation to roads with high metric reach, with the exception of very large-scale developments such as the Perimeter Mall area, which are drawn not by locally high levels of directional reach, but by the globally well-connected freeways which border it on two sides. It seems in Perimeter Center, commercial activity is closely restricted to major roads, except when large-scale development transforms an entire district. In Decatur, on the other hand, several centers represent an historic process of network intensification along well-connected roads. Others reflect patterns of development along linear corridors without network intensification, and others still reflect a larger scale modification of the first pattern, with superblocks surrounded by well-connected streets.

These patterns are common in Atlanta among both older centers and newer, large-scale malls. The quantitative analysis that follows is an attempt to quantify these patterns, and measure how metric and directional reach correlate with areas of commercial intensity.

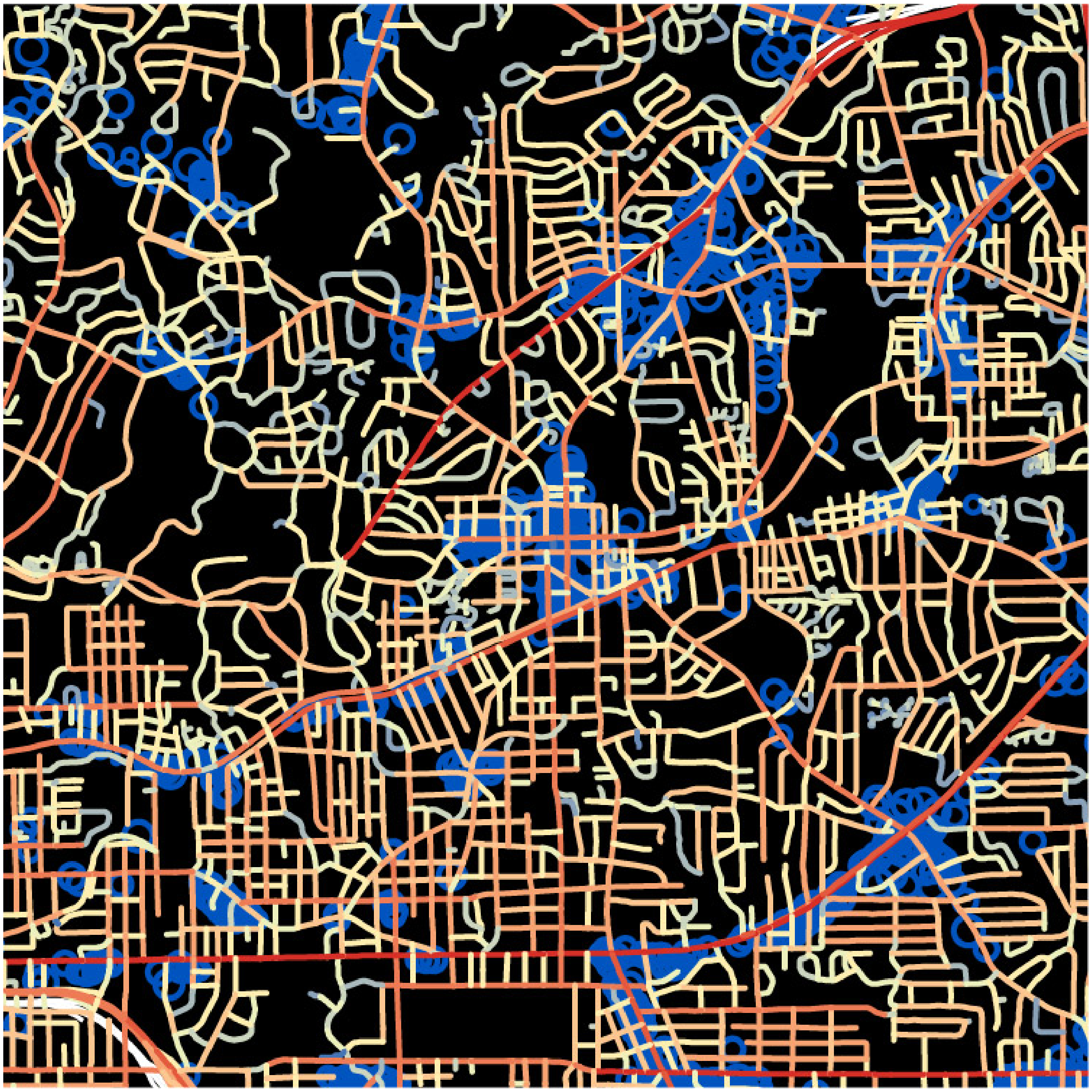

Figure 26: Directional reach in Decatur, 0 turns, all roads

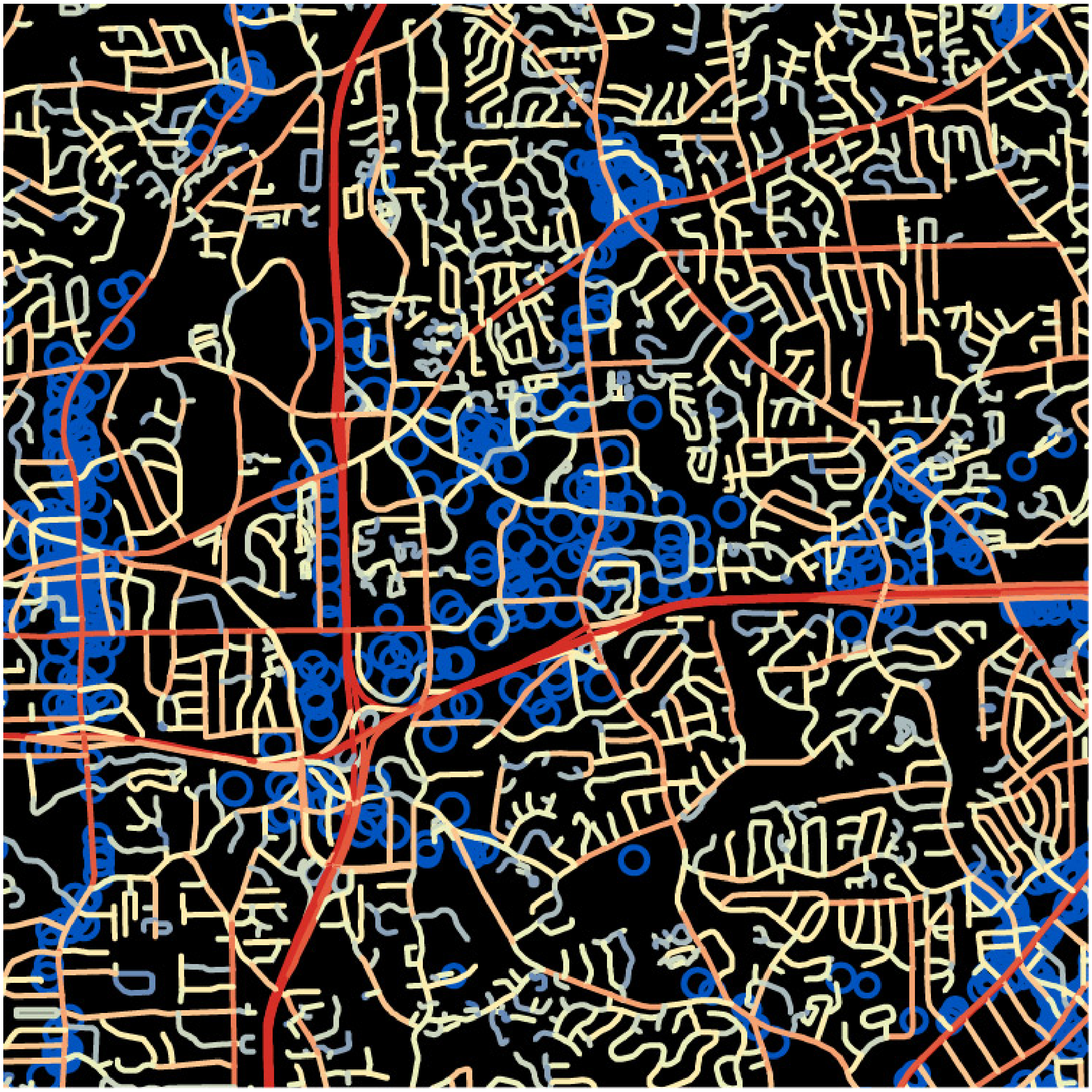

Figure 27: Directional reach in Perimeter Center, 0 turns, all roads

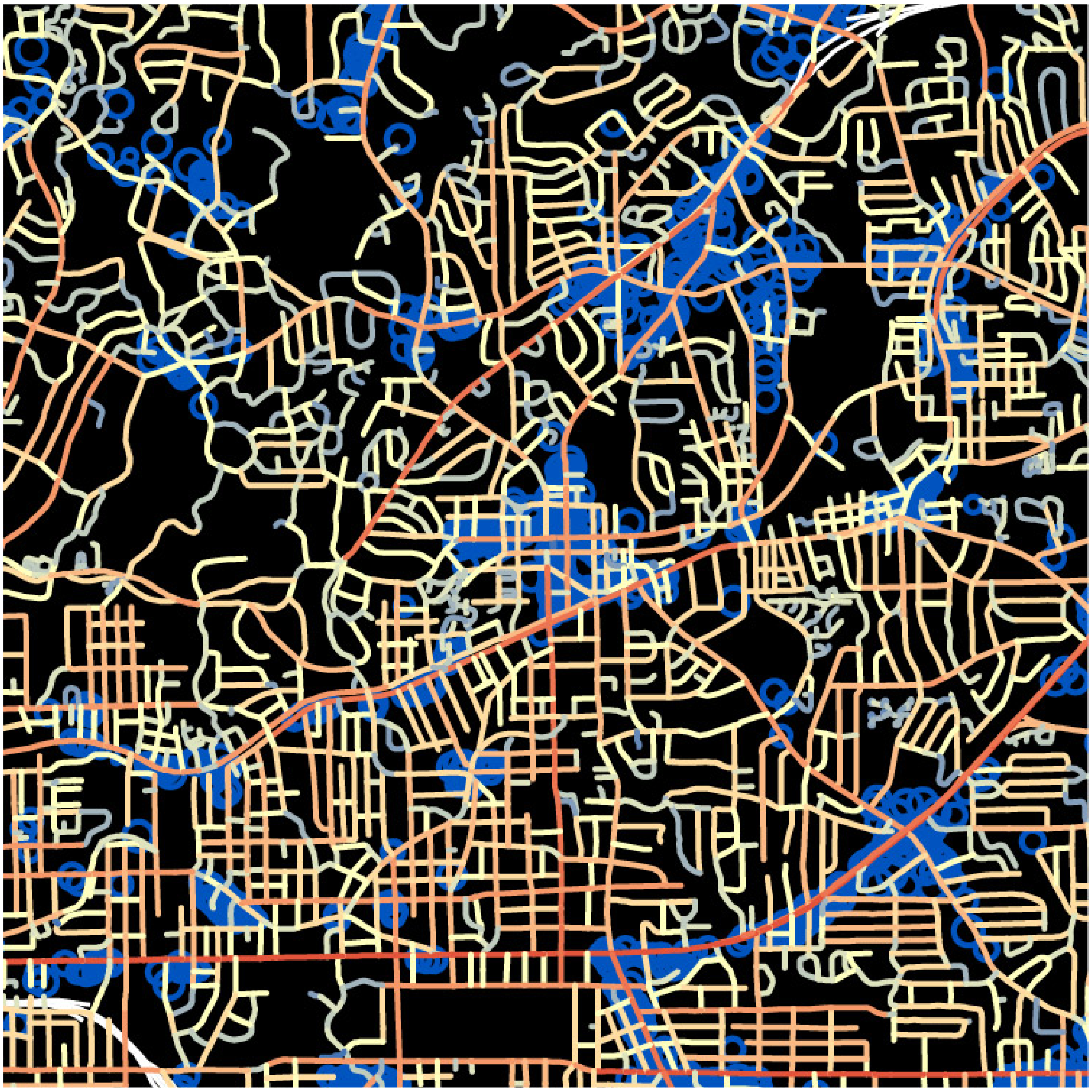

Figure 28: Directional reach in Decatur, 0 turns, Local roads

Figure 29: Directional reach in Perimeter Center, 0 turns, Local roads

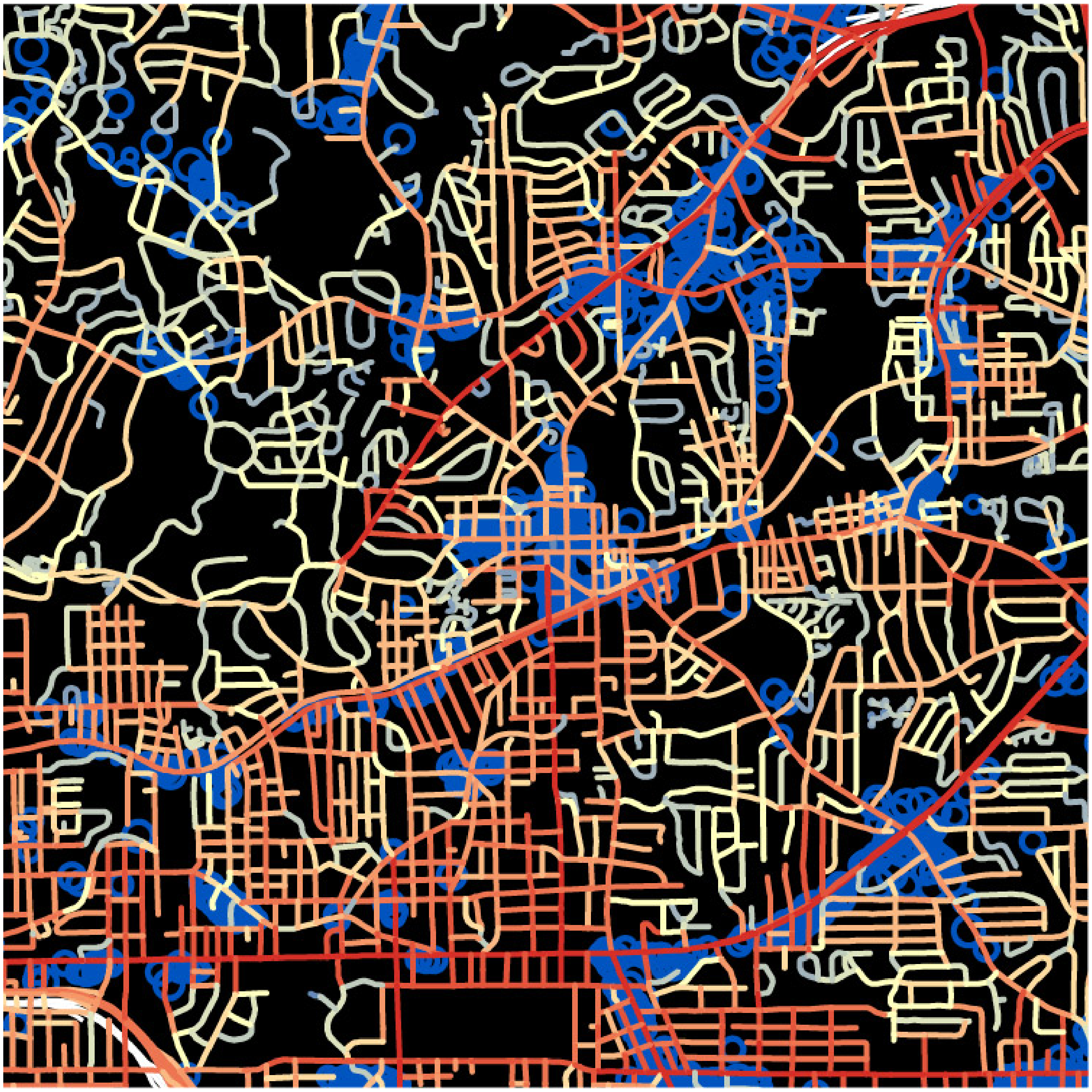

Figure 30: Directional reach in Decatur, 2 turns, All roads

Figure 31: Directional reach in Perimeter Center, 2 turns, All roads

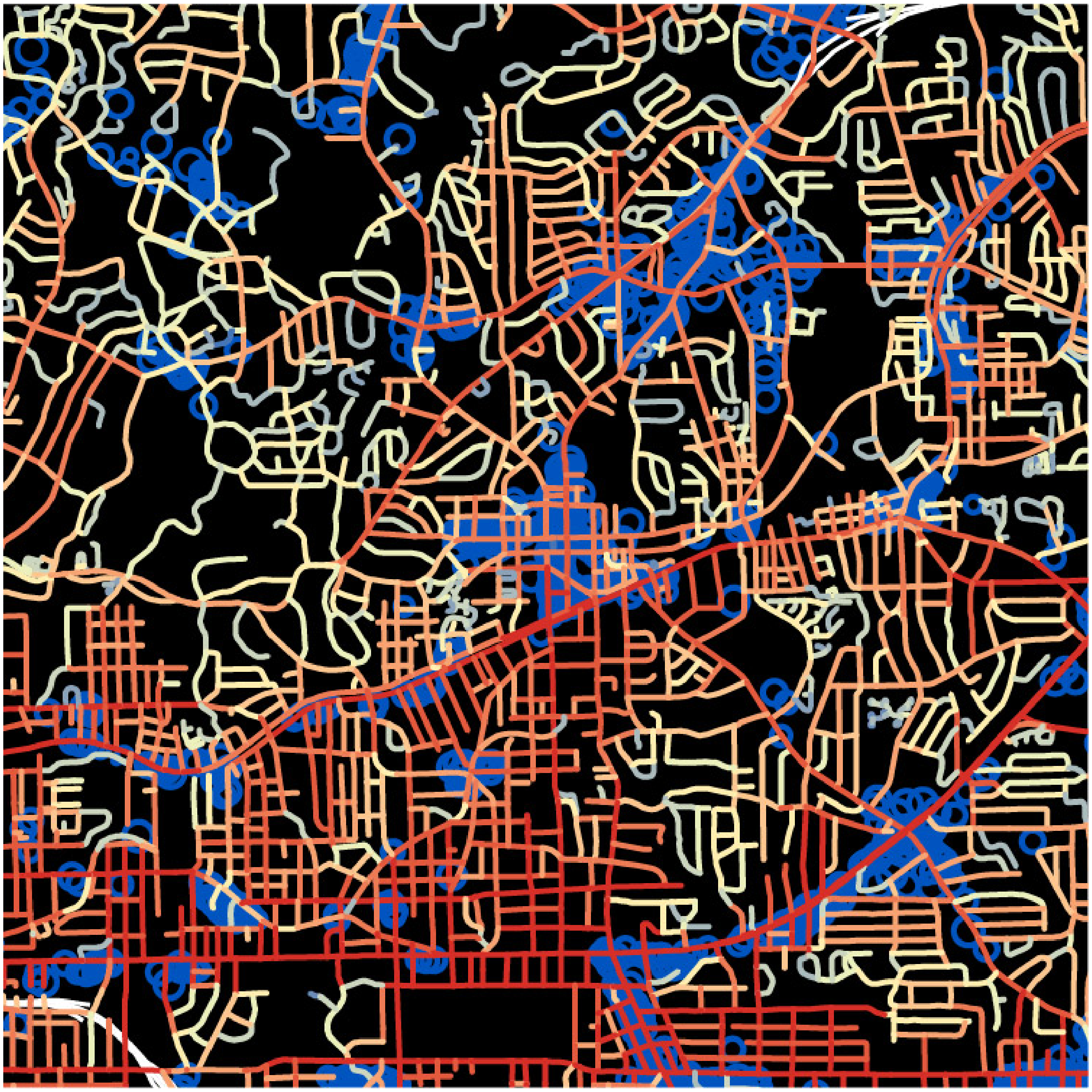

Figure 32: Directional reach in Decatur, 2 turns, Local roads

Figure 33: Directional reach in Perimeter Center, 2 turns, Local roads

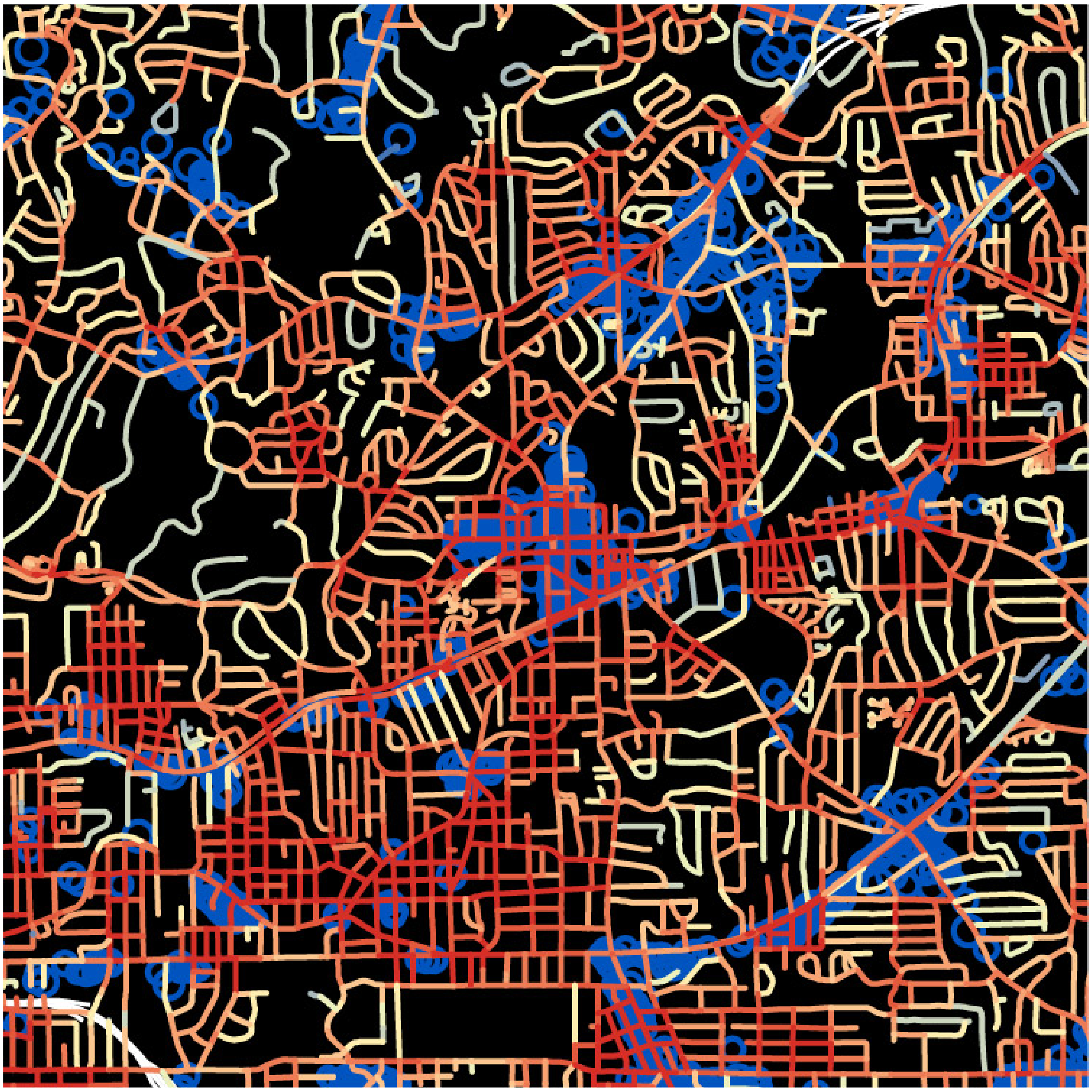

Figure 34: Metric reach in Decatur, 0.25 mile radius, Local roads

Figure 35: Directional reach in Perimeter Center, 0.25 mile radius, Local roads

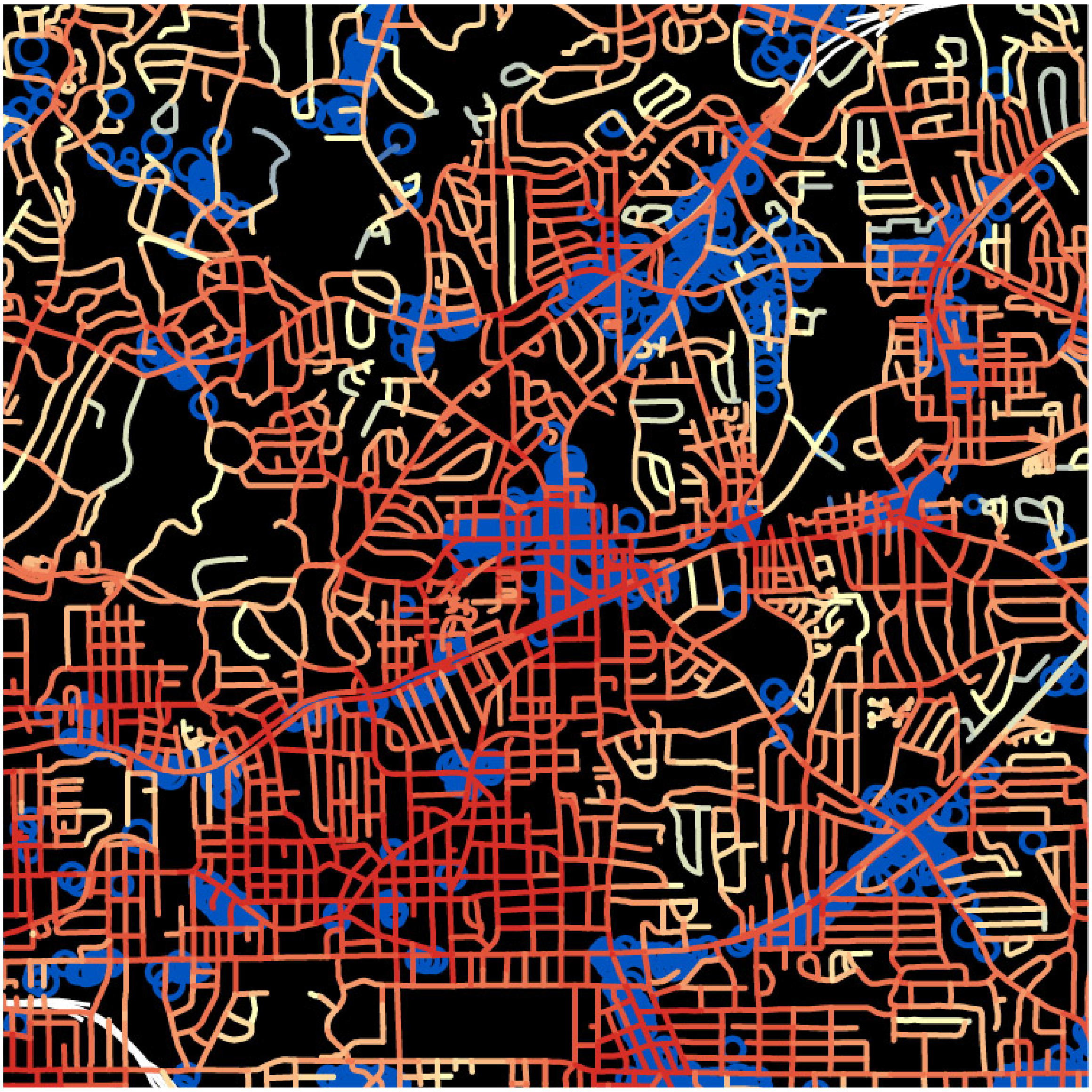

Figure 36: Metric reach in Decatur, 0.50 mile radius, Local roads

Figure 37: Directional reach in Perimeter Center, 0.50 mile radius, Local roads

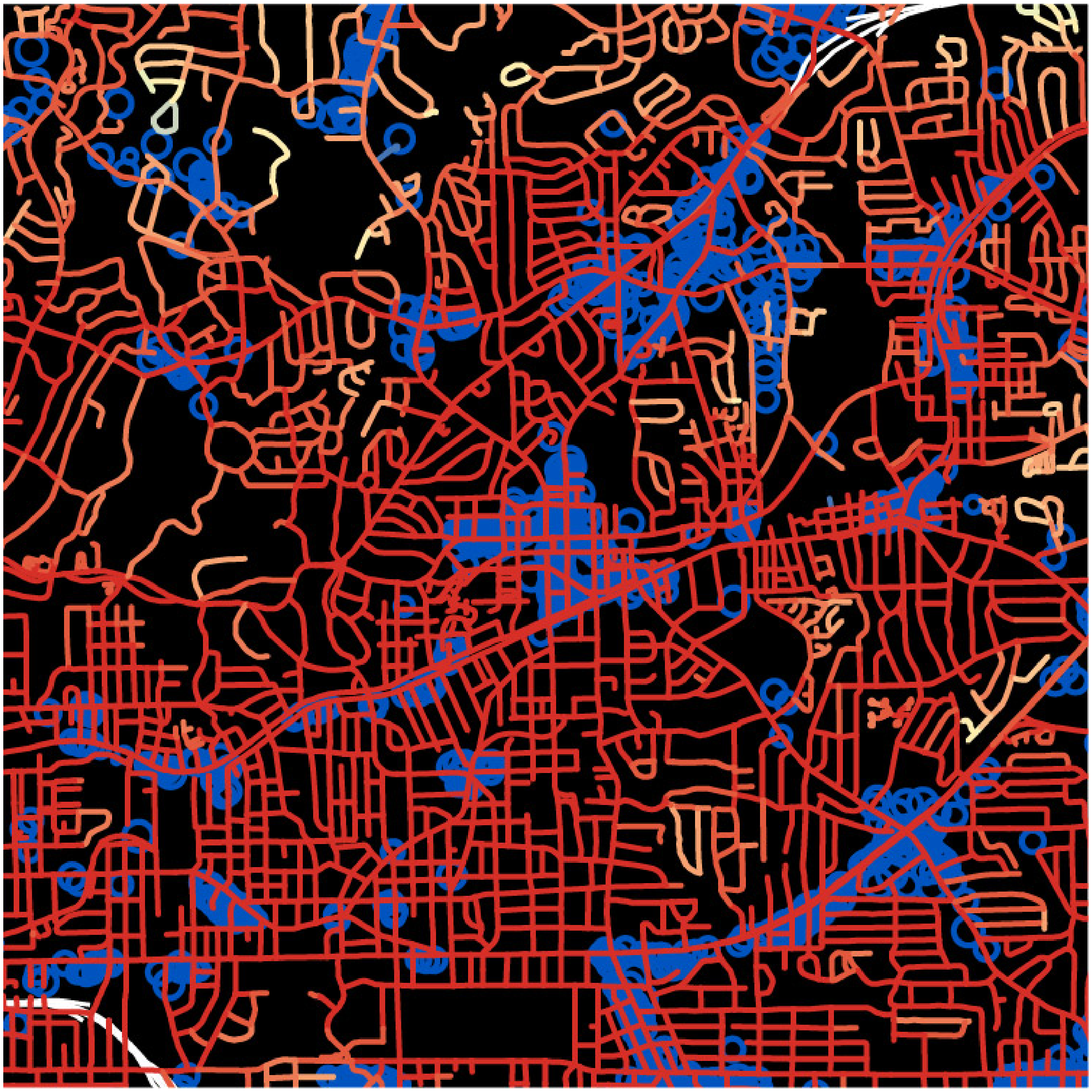

Figure 38: Metric reach in Decatur, 1.0 mile radius, Local roads

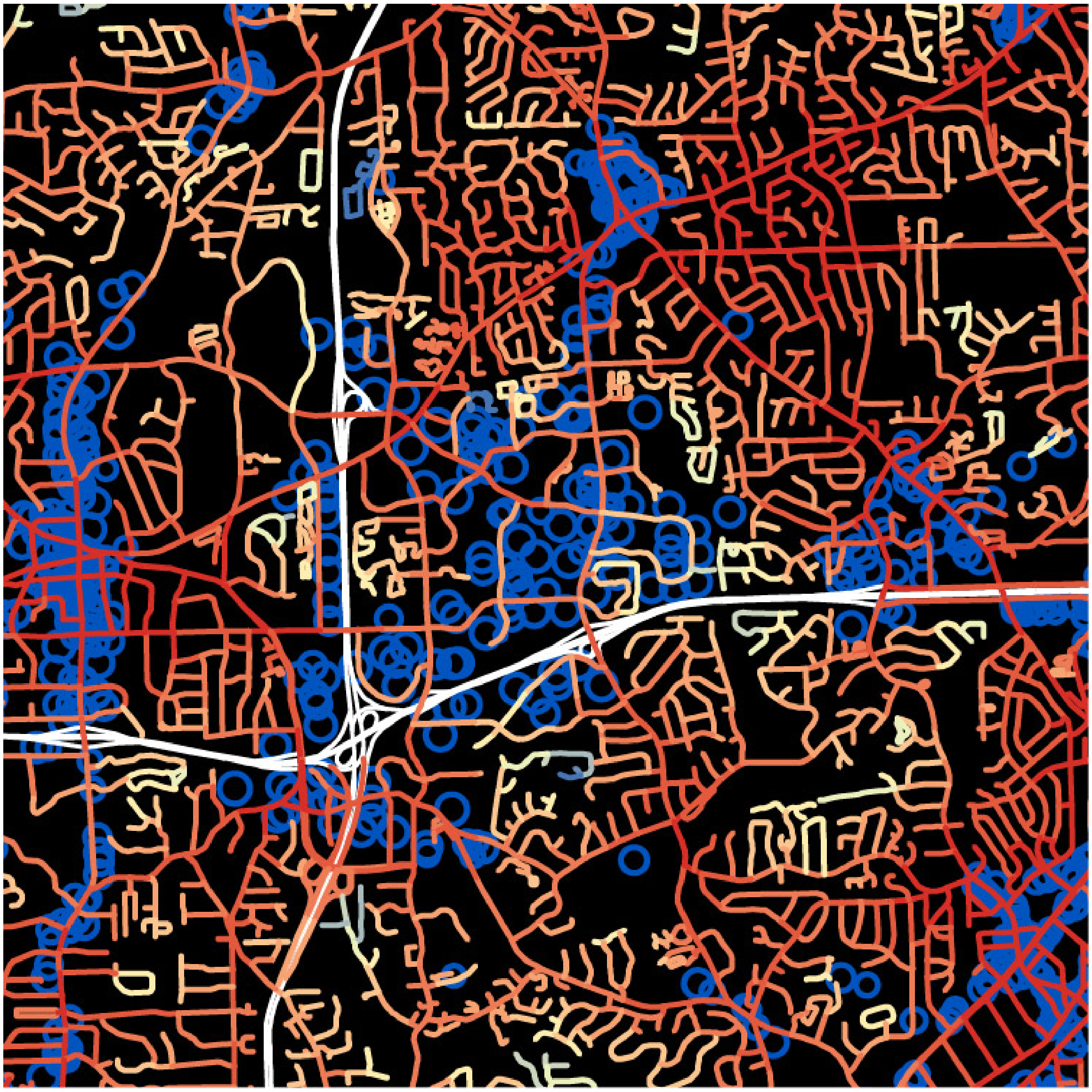

Figure 39: Directional reach in Perimeter Center, 1.0 mile radius, Local roads

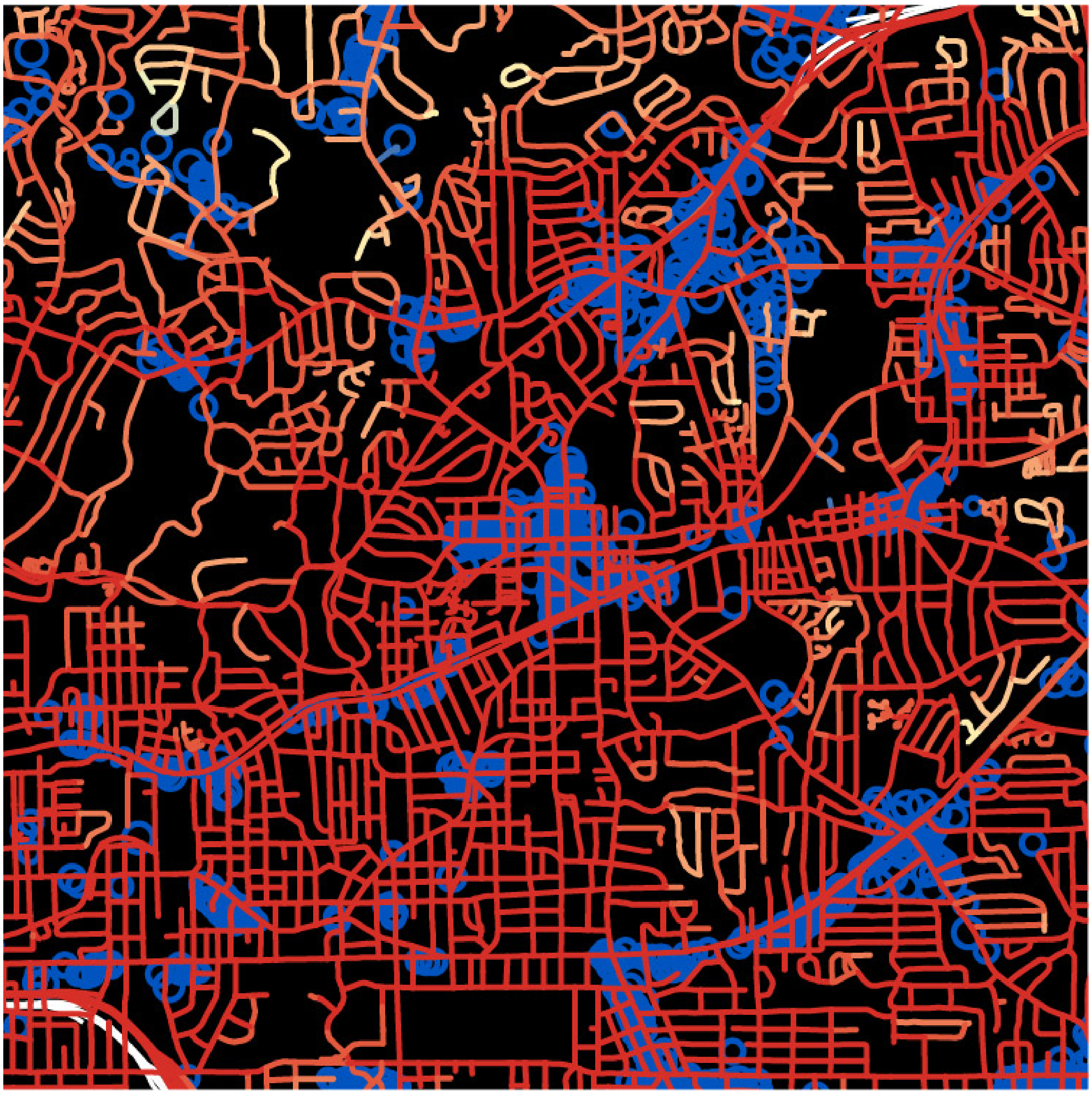

Figure 40: Metric reach in Decatur, 1.0 mile radius, All roads

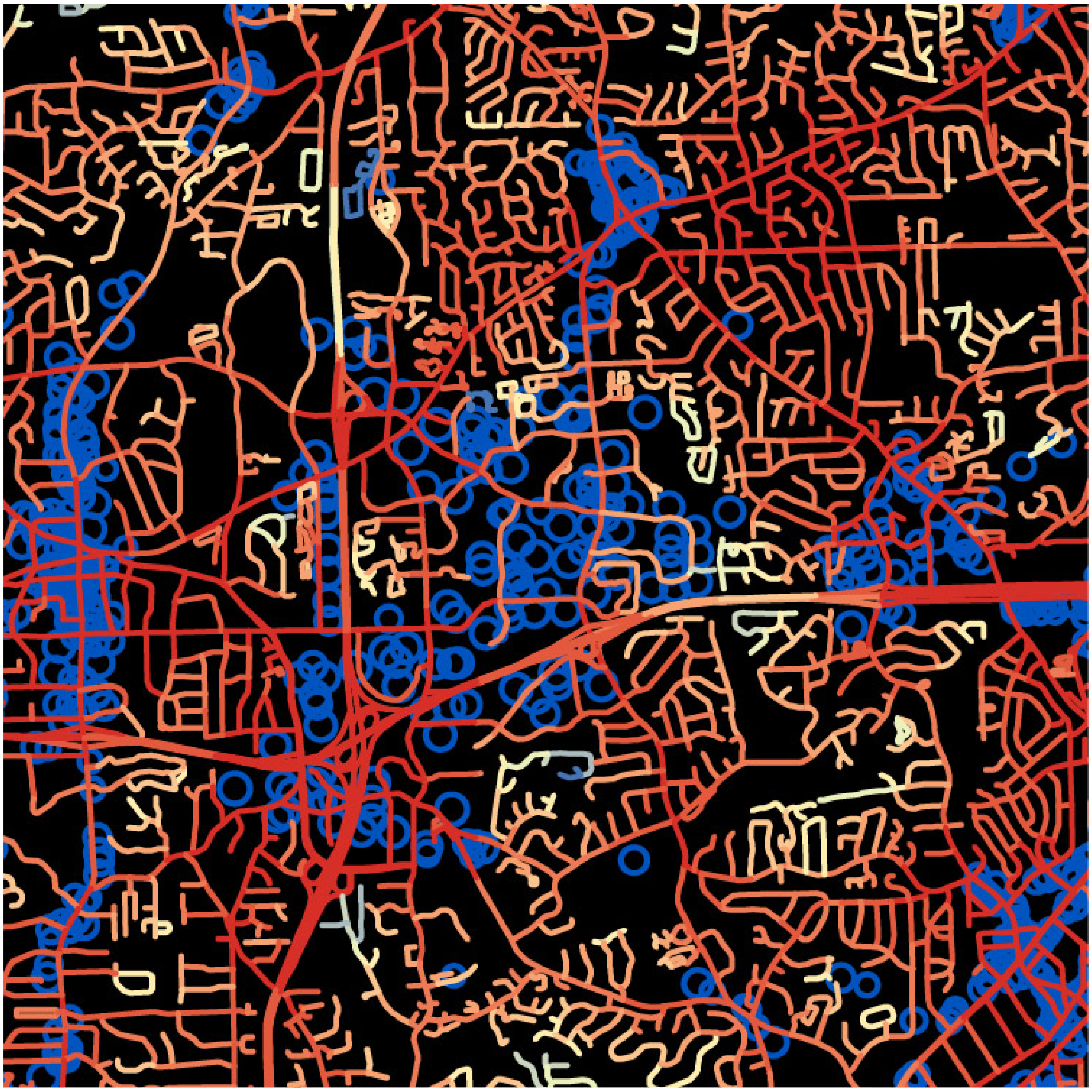

Figure 41: Directional reach in Perimeter Center, 1.0 mile radius, All roads

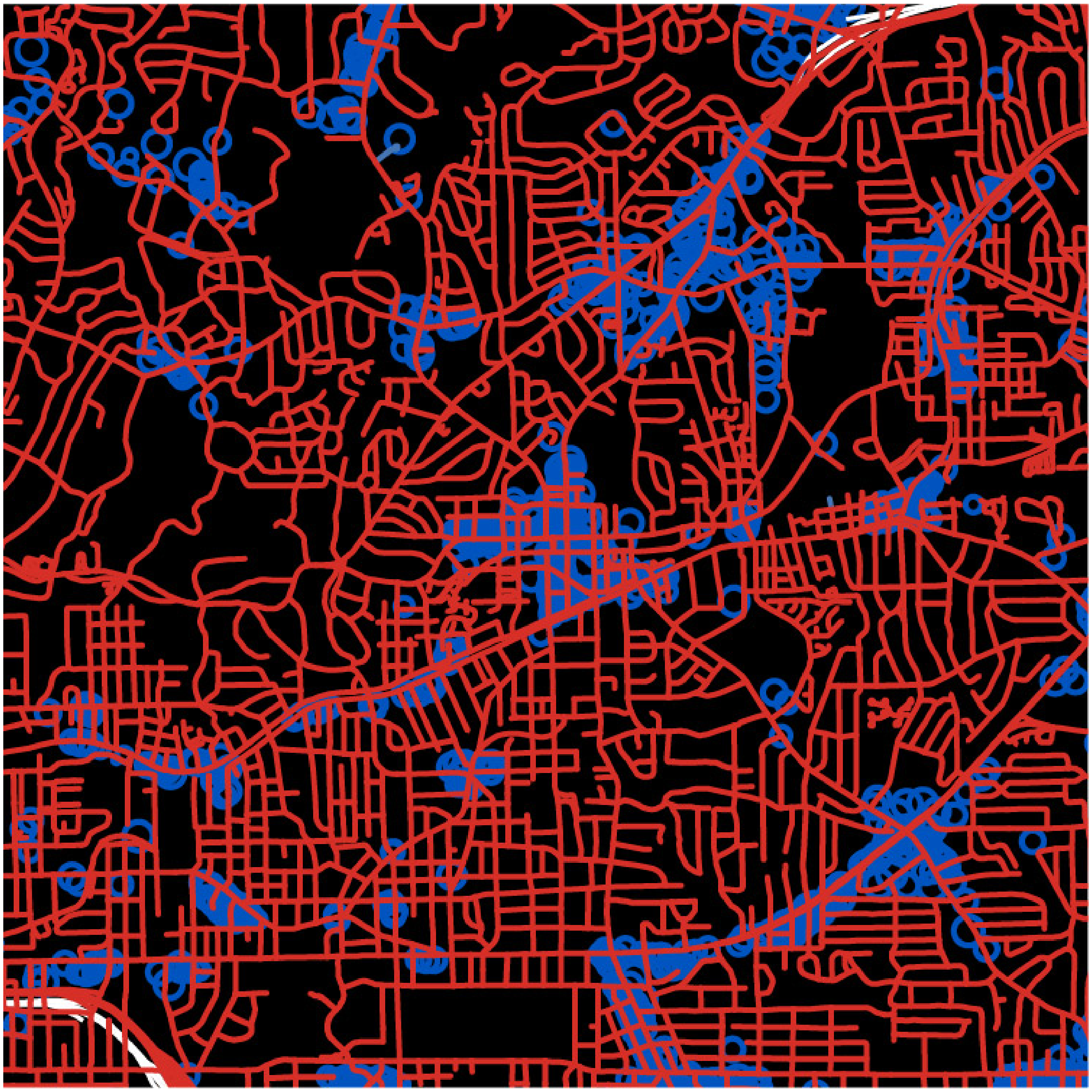

Figure 42: Metric reach in Decatur, 5.0 mile radius, All roads

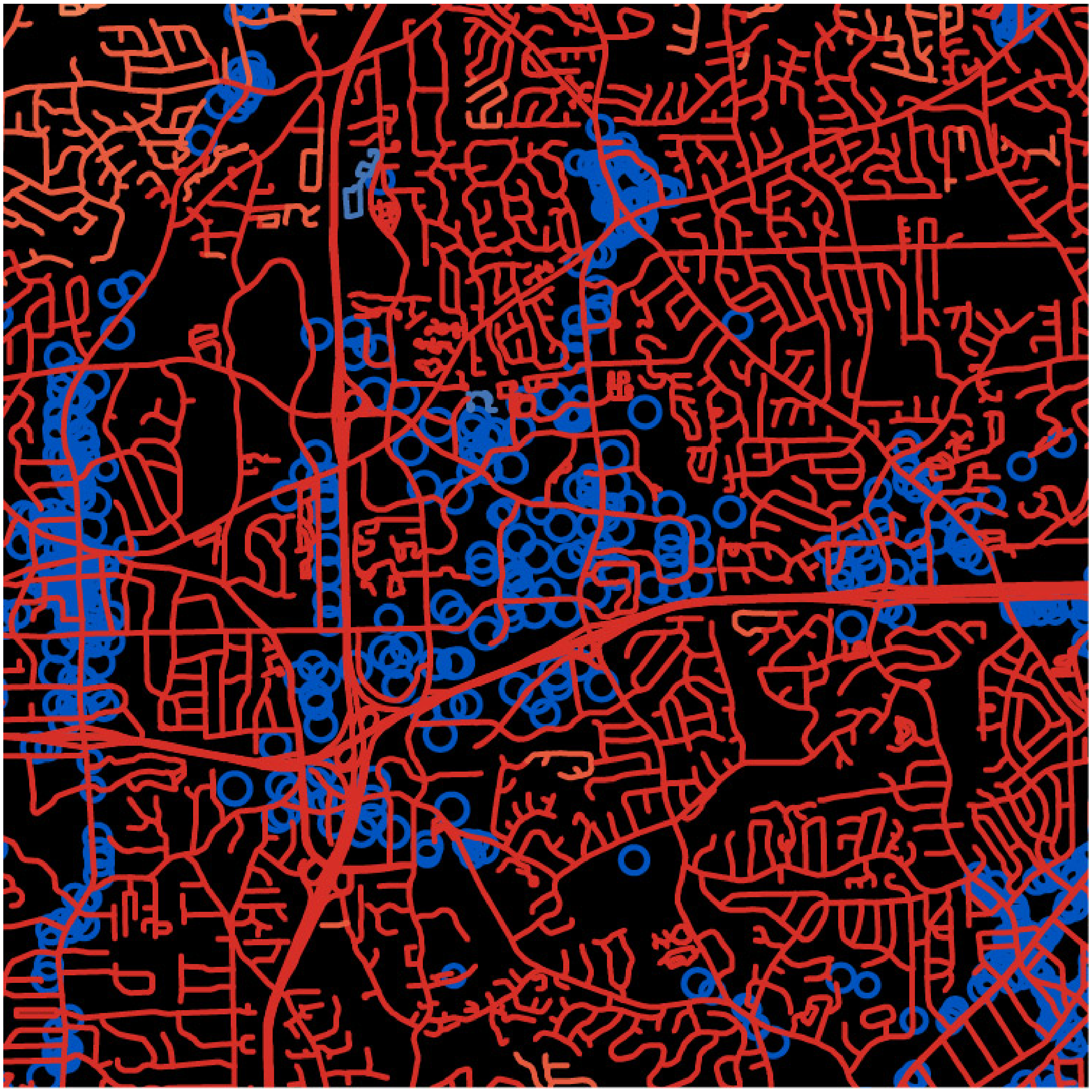

Figure 43: Directional reach in Perimeter Center, 5.0 mile radius, All roads

4.3 Reach Percentiles Analysis

To better understand how each center relates to its surrounding market area, we undertook a brief analysis to compare the reach values of the road nearest each center to the reach values of each other road in that center's market area. For each center and reach value, we calculated the *reach percentile*, defined as the percentage of road length with lower reach values than the road nearest the center (the "central road"). That is:

$$\textit{Reach Percentile} = \frac{\textit{Length of roads with lower reach value than central road}}{\textit{Total length of roads in center} - \textit{Length of central road}} \tag{3}$$

The reach percentile indicates where the in distribution of all reach values the central road's reach value falls. To correct for centers with few roads, we removed the length of the central road from the analysis. This analysis was performed on the set of 0.5 mile bandwidth centers, as smaller centers often have too few roads to produce an acceptable percentile.

Table 2: Mean reach percentile, standard deviation, and number of centers for each of the nine reach metrics. For further detail see histograms in Figure 44 and Figure 45.

	Mean	**Standard Deviation**	**N**
DR0_All	61.5%	29.2%	1441
DR2_All	64.6%	29.7%	1441
DR0_Local	63.2%	29.2%	1441
DR2_Local	66.3%	29.7%	1441
MR025_Local	54.5%	30.1%	1413
MR050_Local	60.8%	29.3%	1413
MR100_Local	66.7%	27.8%	1413
MR100_All	67.6%	27.3%	1413
MR500_All	70.2%	24.5%	1413

The results of this analysis are shown in Table 2. Figures 44 and 45 contain histograms showing the distribution of the reach percentiles for each reach metric. While it is clear that centers tend to fall along roads with higher directional reach values, centers have a wide range of reach percentiles, from 0 to 100 for each reach

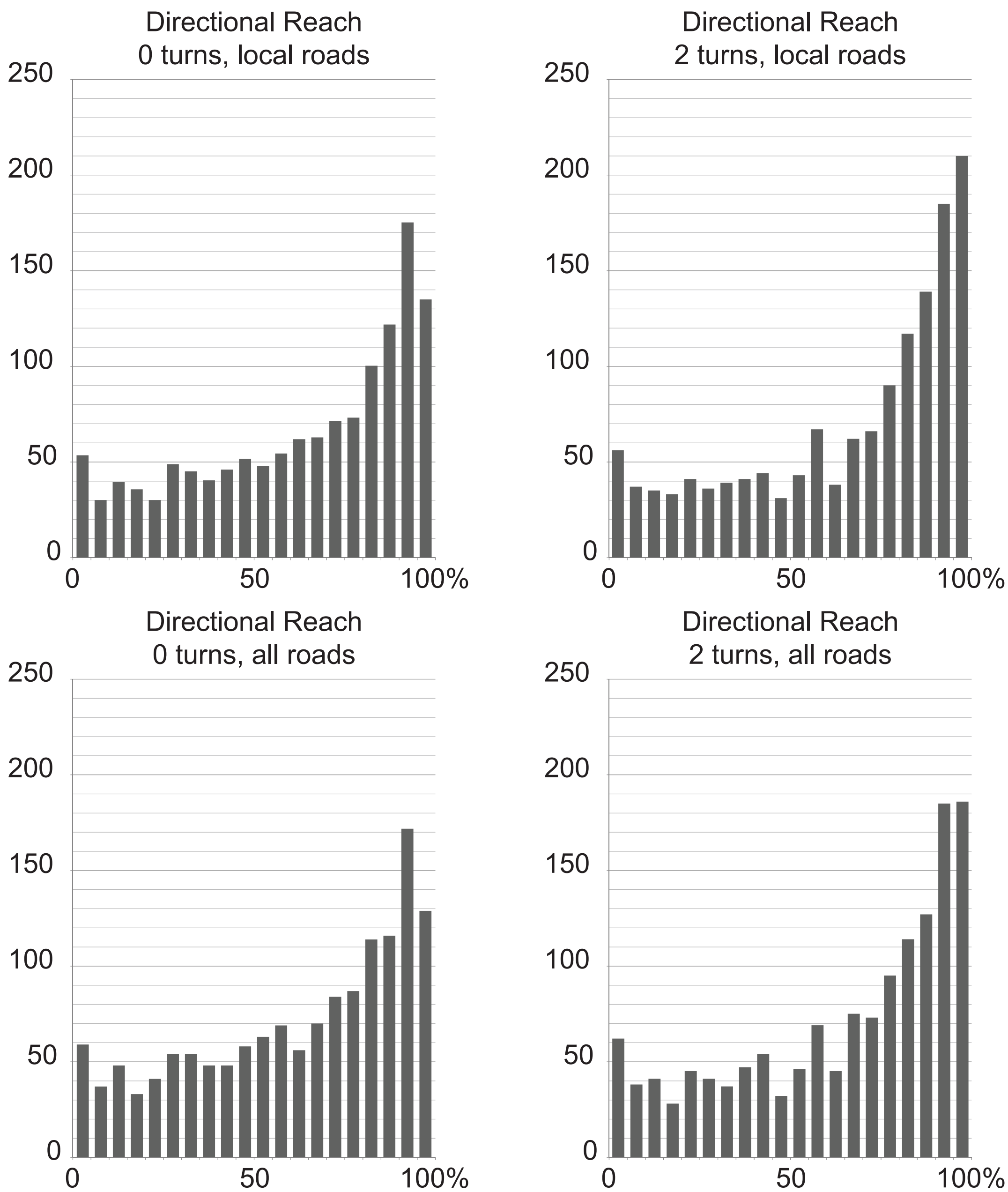

Figure 44: Histograms illustrating the distribution of reach percentiles for four directional reach measures. The *reach percentile* is the percent of roads within each center's market area with a smaller reach value than the nearest road to the center.

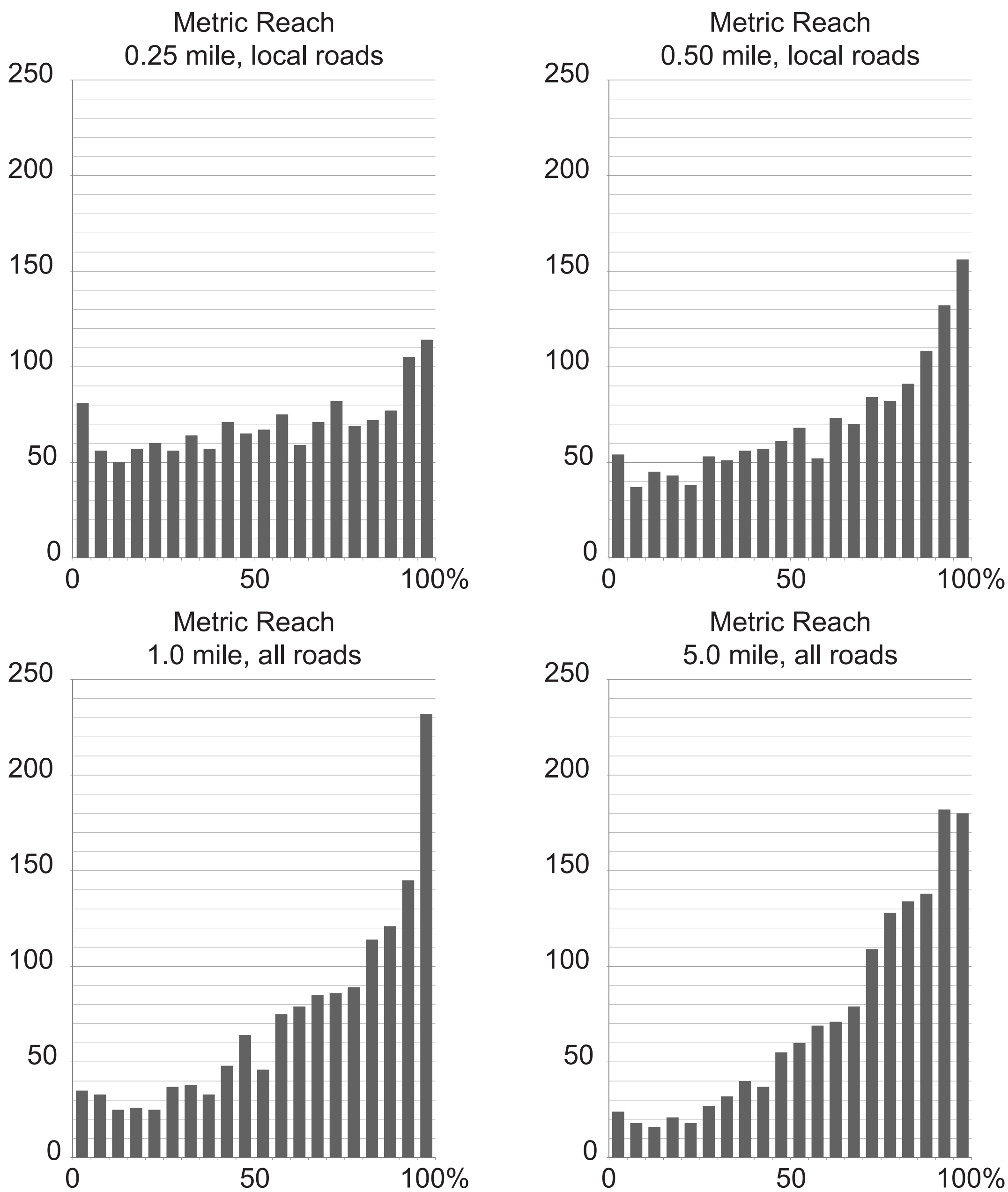

Figure 45: Histograms illustrating the distribution of reach percentiles for four metric reach measures. The *reach percentile* is the percent of roads within each center's market area with a smaller reach value than the nearest road to the center.

measure. The large standard deviations in Table 2 reflect this. Among the directional reach metrics, the two two-turn measures have higher average reach percentiles than the zero-turn measures, suggesting that roads that are long and well-connected to other long well-connected roads may draw an intensity of commercial activity better than roads that are only long themselves. In Atlanta, where many main arteries are curvilinear, this makes intuitive sense.

The distribution of reach percentiles for the metric reach measures is less intuitive. The 0.25 mile bandwidth centers in particular show almost no pattern, with reach percentiles falling evenly over the entire histogram. Larger radius measures have consistently higher reach percentiles, with metric reach with a 5.0 mile radius having the largest of all. This suggests that within each center's market area, centers are more drawn toward roads that are part of a dense network on a global scale than to those that are only part of a small, local intensification of the road network.

4.4 Linear Regression Analysis

The reach percentile analysis provided a description for how centers tend to locate within their market areas, that is, why a center is located on a certain street rather than the street several blocks away. Yet it is equally interesting to determine why a center locates in a given area at all. That is to say, why are centers distributed around the city as they are? Why are some areas privileged with many centers while other areas are deprived?

To address these questions, we then performed a series of linear regression analyses to measure the correlation between commercial intensity (the dependent variables) and urban form measures (the independent variables). For each combination of independent and dependent variables, we determined a Pearson correlation coefficient, R, a slope, B, and a statistical significance, P, for the corresponding linear regression. We then repeated for the natural logarithm of the independent variable, the natural

Table 3: Number of centers per bandwidth, for the entire Metropolitan Atlanta study area and for only the City of Atlanta

	Centers	
Bandwidth	Metro	Atlanta
0.125	4788	380
0.25	2827	215
0.5	1449	87
1	624	25
2	204	5
4	58	2
8	9	0
16	1	0

logarithm of the dependent variable, and the natural logarithm of both.

We performed these linear regression analyses two times. First we used the set of all centers, categorized by KDE bandwidth. Then we used only the centers located in the City of Atlanta, categorized by bandwidth. This allowed us to compare the morphological properties of the entire metropolitan area to the properties of its most urban part. The totals for each row in Table 3 describe the number of centers used at each bandwidth.

For nearly all combinations of independent and dependent variable, taking the natural logarithm of each produced the highest correlation coefficient. We will use this $ln(y) \sim ln(x)$ version, and we will square it to calculate an R^2 for each set of independent and dependent variables. We will use the $ln(y) \sim ln(x)$ R^2 value consistently in this analysis.

Because our analysis included many variables and many methods of quantifying the properties we are studying, it was important to remove as many factors as possible from our analysis. The three methods of measuring the dependent variables produced very similar correlation coefficients. Since the values are similar for each dependent variable, we will use kernel density volume consistently. It is the most descriptive measure of commercial intensity, describing both magnitude and breadth of activity for each center.

To further reduce the complexity of this section, we will discuss the results from only the 0.5 mile, 1.0 mile, and 4.0 mile bandwidths. They provide a representative sample of the eight bandwidths, and they correspond to measures of urban movement: 0.5 miles is a ten-minute walking distance, 1.0 miles is a maximum walking distance, and 4.0 miles is a standard ten-minute drive. The results of the analysis for the remaining bandwidths are reported in the appendix, in section B.1.

In the following analysis, we compare two value from each analysis – R^2 and B. The R^2 value gives a measure of the correlation between the two variables, telling us what percentage of the change in the dependent variable matches the change in the independent variable. It indicates the degree to which the regression model fits the data. A simplified description is that an R^2 of 0.65 indicates that the model explains 65 percent of the variation of the data. An R^2 value of 0 would indicate that there was no relationship between the two, and an R^2 value of one would indicate a perfect relationship between the two. Regression models with higher R^2 values better describe the data studied and indicate a closer connection between the independent and dependent variables. In short, R^2 indicates the appropriateness of the model in describing the data.

The B value is the slope of the best-fit line produced by the linear regression. It gives an indication how large the change in the dependent variable is for a change in the independent variable. For these regressions, a high value of B indicates that a small increase in reach corresponds to a large increase in commercial intensity. A negative B indicates that an increase in reach corresponds to a decrease in commercial intensity. Regression models with large B values indicate that the independent variable (reach) has a stronger effect on the dependent variable (commercial intensity). So B indicates the strength of the model.

The tables below also include P, the statistical significance. P indicates the likelihood a model could have occurred by chance. A P value of 0.0 is best, indicating zero likelihood that the model occurred by chance. P values of 0.05 or larger are generally too large to consider reliable.

4.4.1 Analysis: Entire Metropolitan Atlanta

Our analysis of all centers in metropolitan Atlanta produced a number of interesting results. A first observation is that metric reach (shown in Table 5) is consistently better-correlated with commercial intensity than directional reach (shown in Table 4). For each bandwidth, nearly every metric reach correlation is greater than nearly every directional reach correlation. Additionally, the correlation between commercial activity and metric reach consistently increases as KDE bandwidth increases from 0.50 miles to 4.0 miles.

Table 4: Results of linear regression analyses for each directional reach measure and bandwidth. R^2 is the correlation coefficient, B is the slope derived from the regression, and the statistical significance, P, of each regression is indicated by: ** $P < 0.01$; * $P < 0.05$. See Table 10 for additional bandwidths

		Bandwidth		
		0.5	1	4
$ln(DR0A\_max)$	R^2	0.20**	0.27**	0.46
	B	0.99	1.34	2.30
$ln(DR0L\_max)$	R^2	0.08**	0.10**	0.32**
	B	0.89	1.16	3.06
$ln(DR2A\_max)$	R^2	0.31**	0.38**	0.53**
	B	0.96	1.19	1.90
$ln(DR2L\_max)$	R^2	0.15**	0.19**	0.35**
	B	0.91	1.19	2.22

Several patterns emerge from the results of the directional reach analyses. The two analyses performed on the set of all roads each have stronger R^2 values than the corresponding analyses performed on the set of non-freeway roads. They also have

Table 5: Results of linear regression analyses for each metric reach measure and bandwidth. R^2 is the correlation coefficient, B is the slope derived from the regression, and the statistical significance, P, of each regression is indicated by: ** $P < 0.01$; * $P < 0.05$. See Table 10 for additional bandwidths

		Bandwidth		
		0.5	1	4
$ln(MR025L\_mean)$	R^2	0.27**	0.45**	0.66**
	B	4.88	7.60	11.64
$ln(MR050L\_mean)$	R^2	0.29**	0.47**	0.70**
	B	3.53	5.23	7.80
$ln(MR100L\_mean)$	R^2	0.36**	0.51**	0.75**
	B	2.97	3.88	5.49
$ln(MR100A\_mean)$	R^2	0.32**	0.49**	0.75**
	B	2.91	4.00	5.74
$ln(MR500A\_mean)$	R^2	0.32**	0.46**	0.72**
	B	2.30	2.75	3.06

similar, but slightly larger B values for the 0.5 miles bandwidth, but smaller B values for the 4.0 mile bandwidth. For the 4.0 mile bandwidth, the two zero-turn analyses have the highest b-values. These patterns suggest that a road well-connected to freeways has a slight positive effect on the size of a small commercial center compared to a similar location on a well-connected road not connected to freeways. However the difference in B is small.

We can derive similar conclusions by analyzing the metric reach results. For all bandwidths, metric reach with a 0.25 mile radius and a 0.50 mile radius have the smallest R^2 values. Yet they have the two largest B values for all bandwidths. This suggests that while there is great variation in terms of local network density among the set of all centers, having a dense street network at all scales can have a larger positive effect on a center than any other form of network intensification.

These patterns suggest a number of relationships between commercial intensity and urban form. First, they suggest that the density of the road network is nearly always more closely correlated with the size of a commercial center than is a commercial center's connection to long, well-connected roads. This is reflected in the consistently larger values of both R^2 and B for metric reach models compared to directional reach models. These two measures of reach reflect different sorts of connectivity, developed separately. As Hillier describes, global processes draw activity to locations on long, well-connected roads initially, which produces further intensification of the local road network. Thus our analysis suggests that local-scale network intensification, as described by metric reach with a 0.25 mile radius, is the primary result of an increase in center size. Further, it follows that directional reach measures would have lower R^2 and B values, because directional reach would not increase as the size of a center increases in Hillier's model. Rather, the presence of long, well-connected roads draws activity on on a local level; that is, commercial centers tend to locate on these roads rather than less-connected roads within their own market areas, as described in section 4.3. On the other hand, metric reach would tend to increase substantially as the size of a center increased, as new roads are added to open up new land to development, as described in 4.2.2.

4.4.2 Analysis: City of Atlanta

The correlations produced between the dependent variables of commercial intensity and the independent variables of urban form were then calculated for only the centers located within the city limits of Atlanta. These correlations, shown in tables 6 and 7, are similar in several aspects to the correlations produced from the analysis of the entire metro area. Again, metric reach correlations are generally stronger than directional reach correlations, and correlations on larger bandwidths are generally stronger than correlations on smaller bandwidths.

The directional reach analyses produce very similar results to the analysis for the

Table 6: Results of linear regression analyses for each directional reach measure and bandwidth, limited to those centers falling within the City of Atlanta. R^2 is the correlation coefficient, B is the slope derived from the regression, and the statistical significance, P, of each regression is indicated by: ** $P < 0.01$; * $P < 0.05$. See Table 11 for additional bandwidths

		Bandwidth	
		0.5	1
$ln(DR0A\_max)$	R^2	0.12**	0.42**
	B	1.12	2.25
$ln(DR0L\_max)$	R^2	0.05*	0.37**
	B	0.87	2.61
$ln(DR2A\_max)$	R^2	0.20**	0.61**
	B	0.99	1.83
$ln(DR2L\_max)$	R^2	0.12**	0.54**
	B	0.83	1.99

Table 7: Results of linear regression analyses for each metric reach measure and bandwidth, limited to those centers falling within the City of Atlanta. R^2 is the correlation coefficient, B is the slope derived from the regression, and the statistical significance, P, of each regression is indicated by: ** $P < 0.01$; * $P < 0.05$. See Table 12 for additional bandwidths

		Bandwidth	
		0.5	1
$ln(MR025L\_mean)$	R^2	0.21**	0.41**
	B	2.99	5.72
$ln(MR050L\_mean)$	R^2	0.21**	0.48**
	B	2.36	4.70
$ln(MR100L\_mean)$	R^2	0.29**	0.60**
	B	2.52	4.21
$ln(MR100A\_mean)$	R^2	0.21**	0.54**
	B	2.17	4.25
$ln(MR500A\_mean)$	R^2	0.18**	0.47**
	B	3.28	5.21

entire metropolitan area. For both bandwidths, R^2 are larger for the two models using the set of all roads than on the set of non-freeway roads. The B values are larger for the two models using all roads at the 0.5 mile bandwidth, but are smaller for these models at the 1.0 mile bandwidth. With only two bandwidths to analyze, it is difficult to determine a pattern, but this may suggest that smaller scale centers are slightly more closely tied to being well-connected to a freeway than are larger-scale centers.

Metric reach analyses also show a similar pattern to the measurements for the entire metropolitan area. Again the metric reach with smaller radii have both smaller R^2 values and larger B values. Curiously, metric reach with a 5.0 mile radius has very large b-values within the city of Atlanta. Given the smaller number of centers included in this analysis, this variation can be considered an anomaly. Generally, this analysis of centers within Atlanta indicates that the connection between urban form, represented by the reach measures, and commercial intensity operates similarly both within Atlanta and in its suburbs.

In both the City of Atlanta and all of Metropolitan Atlanta, higher street densities (as quantified by metric reach) are associated with higher levels of commercial activity. Long, well-connected roads (as quantified by metric reach) also show a positive correlation with an increase in levels of commercial activity. These measures suggest that the growth of commercial centers in Atlanta follows a pattern similar to Hillier's observations in London and York, in which global processes decided where a center would form, while local processes guided the intensification of the center's grid.

CHAPTER V

CONCLUSION

5.1 Background: Centrality

In this paper we examined the pattern of centrality in Atlanta extensively. An extensive dataset of land use in Atlanta allowed us to use multiple quantitative analyses to examine how commercial centers distribute both in all space and within the immediate area. With these studies we both illustrated the pattern of centers in Atlanta and described the dual attraction of centers to both dense road networks and long, well-connected roads.

Urban space is organized so as to provide access from all parts of a densely developed area to all other parts. Patterns of accessibility and land use, however, converge onto certain areas which act as concentrations of intense activity and as reference points for circulation and orientation. Thus, we can speak of urban space as having one or more centers. Centers are defined at different scales. Some dominate over large areas and some are relevant only within a local context. Traditional centrality theory postulates that centers are organized hierarchically, with a dominant main center associated with each city and increasing numbers of smaller centers associated with city parts. More recent approaches look at centrality as a continuous process of formation which is governed by patterns of urban growth and change on the one hand, and by the propensity of the street network to make some locations more accessible than others. Researchers in the field of space syntax have begun to formulate a comprehensive theory of how urban form and function are generated. This paper sought to examine the outcome of this theory in the specific context of Atlanta.

5.2 Data and Methods

In this thesis, the distribution of commercial and office space served as a proxy for the distribution of activity in the city. In general, our sense of urban liveliness and intensity is associated with centers of employment or trade, with residential areas tending to be less dense, and to generate less internal movement, at least in the USA.

The distribution of commercial and office square footage in a ten-county region containing the core of Metropolitan Atlanta was analyzed in order to identify centers of activity and study their spatial distribution. The land-use data was provided by the SMARTRAQ data base produced by the GIS center in Georgia Tech in 2003. The analysis was preceded by data correction (for discrepancies between the SMARTRAQ and tax records as well as for duplicate values) and data extrapolation for those data point was not explicit provided by the original data source. In addition, the connectivity of the road and street network of Atlanta was analyzed based on the measures of Metric and Directional Reach, in two sets: one using all roads and one excluding freeways and limited access highways from the analysis.

Centrality values were computed for the whole area using a Kernel Density Estimation function. This took each data point (centroid of a parcel) and produces a distribution surface representing the "impact" or the "attraction value" of the parcel as a function of the office and retail square footage plotted against distance in all directions. This method assumes attraction diminishes with increases in distance, reaching zero at a distance r from the centroid, where r is the bandwidth of the kernel density function. For the sake of this analysis, kernel density values were computed for all the centroids of a square 150 meters grid overlaid over the ten-county area. Bandwidths were initially set at the geometric scale of 0.2, 0.4, 0.8, 1.6, 3.2, 6.4, 12.9 and 25.7 kilometers (0.125, 0.25, 0.50, 1, 2, 4, 8 and 16 miles). However, the following bandwidths were of particular interest: 0.25 mile as the radius of most comfortable walking, half a mile as the radius of easily acceptable walking, one mile as the maximum radius of normal walking, two mile as the radius of proximate driving and four miles as the radius of convenient driving. Setting the bandwidth at these values expresses the idea that the "presence" of a commercial or office land use is not relevant for larger distances of everyday navigation.

Based on the above, centers were identified as local maxima on the surface of kernel density values. A 375 meter radius was specified as minimum for the identification of a local peak. Given the local maxima, the area of "dominance" or the "market area" of each center is defined as a polygon over which the center was dominant using a topographic analogy. The polygons were analyzed using GIS tools for delineating watersheds and applying these tools to the kernel density surface.

5.3 The Distribution of Centers over the Surface of Atlanta

The distribution of individual centers is shown in Figure 9. Examination of the Figure suggests several interesting conclusions.

1. Centers at different bandwidths are interspersed with each center of higher bandwidth surrounded by multiple centers of lower bandwidth. However, the pattern is not uniform over all of Metropolitan Atlanta.

2. In some areas, a location is near centers of many bandwidths in multiple directions. Without considering the structure of the street network, we can infer that people living these locations have a wide range of choices as to which centers to use on different occasions. In other areas, however, centers of higher bandwidth stand relatively isolated while surrounding locations offer fewer choices to those living there.

3. The freeways are associated with many centers of higher bandwidth and a large number of centers of lower bandwidth. However, there are also many centers across all bandwidths that are not associated with freeways.

4. Figure 12 summarizes some of these observations. Atlanta is covered by a 2 miles square grid, and the number of centers at any bandwidth for each cell of the grid is counted. By and large, the area surrounded by I-285, the perimeter freeway, contains more centers per grid unit than outlying areas. Additionally, grid units containing large numbers of centers are mostly associated with freeways.

Taken together figures 9 and 12 reveal an intricate pattern of centrality which is described by several spatial distributions: the distribution of kernel density which measures the aggregate impact of overlapping surfaces of attraction associated with specific parcels, the distribution of local maxima at varying bandwidths, the clustering of these maxima in particular areas, and the pattern of proximity of maxima associated with different bandwidths. One of the contributions of the techniques of analysis used in recent literature and in this thesis is to allow centrality to be visualized in a manner that emphasizes these overlapping patterns.

5.4 The Location of Centers in Relation to the Nearby Street Network

The reach values associated with the road segment nearest a center (the "central road") were compared to the reach values of all other road segments in the polygon of dominance of a center. The analysis showed that for 1441 centers, the central road tended to lie in the upper 50 percentile with a plurality of the distribution associated with the 95 percentile. That is, centers gravitate towards road segments in the nearby areas that have the highest connectivity values. For directional reach the effect is as strong for all roads as it is for local roads. For metric reach the effect is strongest when all roads are included. The most consistent effect is for directional reach at two direction changes. This suggests that centers are located on roads that are long and well connected to other long roads.

However, the general conclusion should not obscure divergent trends that are revealed when a specific area is examined in detail. A comparison of Decatur, an old city absorbed into the larger metropolitan fabric, and Perimeter, an emerging edge city, shows that the road network around centers tends to form several common shapes. Sometimes centers are associated with the main roads of a well-connected local road network; sometimes they are associated with critical intersections of roads with high directional reach but not necessarily with a dense local road network; sometimes they are associated with larger urban blocks surrounded by roads of high directional reach. In other words, the association between street connectivity and centrality within dominance polygons can assume alternative modes that may be associated with the process of historical growth of the city. Older centers are more likely to fit the first category, while newer centers are more likely to fit the third.

5.5 *The Relative Kernel Density Volume of Centers in Relation to the Street Network*

For the ten county region, higher kernel densities are associated with more dense street systems, across all three bandwidths of 0.5, 1 and 4 miles. To a lesser extent, higher kernel densities are also associated with locations benefiting from higher directional reach at two direction changes. Furthermore, the association is stronger when street density, as measured by metric reach, is computed at 1 mile radius (Table 5). The same trends apply when the analysis is limited to the City of Atlanta, except that in this case the correlations obtained for directional reach are as strong as those obtained for metric reach. These results suggest that there is a general tendency for the volume of kernel density (that is, intensity of commercial activity) to be associated with areas where street density is higher, and a secondary tendency for the volume of kernel density to be associated with areas where streets are more linearly aligned and thus have a higher directional reach. The secondary tendency takes over in the City of Atlanta where, compared to the region, street density is relatively high.

5.6 Implications

Atlanta is one of the most spread cities in the United States, with larger urban blocks and sparser street intersections than any other major metropolitan area on average. However, and despite some contrary commentary in the literature, Atlanta is characterized by a hierarchical pattern of centrality which is systematically mapped on the spatial structure of the road network.

The analysis brings to the fore the patterns of association between the connectivity of the street network and the distribution of centers. This is hardly a surprising result given the general belief that good access is fundamental to commercial success and important to supporting a large employment base. However, the analysis also highlights the diffusion of centers of different scales across the area, as well as the tendency, within the inner metropolitan area, for a variety of centers of different scales to co-exist within close proximity. Intuition, as well as the difference between inner and outer areas, suggests that the pattern emerges over time; zoning probably reflects the underlying process of centrality as often as it may anticipate it. The physical precondition of the emerging pattern of centrality is the infrastructure of roads and streets. Subdivision regulations that affect the emergence of this infrastructure are as important to the underlying process of centrality as zoning.

The analysis also emphasizes patterns of inequality of access to centers, particularly between the inner and outer areas. The analysis suggests that these patterns of inequality can be moderated by encouraging local intensification of the street network coupled to zoning so as to support the emergence of local centers in areas which are presently deprived of finely grained centrality. However, any more firm recommendations in this regard need to also be supported by a study of the distribution of population. This study is limited by the fact that population density has not been taken into account.

5.7 Summary

The distribution of centrality is associated with the properties of the street network in two ways. At the metropolitan scale, there is a tendency for higher kernel volumes to be associated with denser street networks. Locally, within the polygons of dominance, centers tend to gravitate towards longer roads intersecting many other long roads. In areas where street density is relatively high, such as the City of Atlanta, the gravitation towards longer roads which intersect many other longer roads is quite pronounced at scales larger than the individual dominance polygon.

This analysis has shown that beneath Atlanta's urban fabric, there exists complex logic generating a hierarchical structure of centers at multiple scales. Our results support Bill Hillier's theory that centrality develops by a dual process (Hillier, 2002), including the minimization of distance in the global network (as shown by higher levels of directional reach) and the intensification of street patterns in the local road network (as shown by higher levels of metric reach). Further, the set of centers we generated show that, in at least some areas of Atlanta, Hillier's description of "pervasive centrality" (Hillier et al., 2008) holds true – that "you are close to a small centre and not far from a much larger one".

Like all cities, Atlanta exhibits a complex pattern of activity. That its network of centers is drawn to large infrastructure confirms rather than denying it's urbanity. This thesis has shown that in Atlanta, as in all urban places, the hierarchy of centers goes all the way down, forming layers of meaning upon layers of meaning, and providing the complexity necessary for good, urban life..

APPENDIX A

SCALING LAW ANALYSIS

A.1 Introduction

Research into the structure of urban form has suggested that the form of cities, like organisms, exhibit patterns of scaling, such that urban form at a given scale is related to urban form at larger and smaller scales by simple rules. The most widely understood of these is Zipf's Law (Zipf, 1949), which states that the probability that a city has a population greater than P is proportional to $1/P$ (Gabaix, 1999). That is, there are many small cities but few large cities. More specifically, Zipf found that this distribution could be plotted, with the *log* of the population on the x axis and the *log* of the rank on the y axis, and the curve would have a slope of -1. The distribution described by Zipf is a power law with an exponent of -1. That is, it resembles:

$$p(r) = r^{-\beta} \tag{4}$$

where $p(r)$ is probability density function representing the distribution of sizes for rank r. Here β is known as the *power* of the power law (Batty et al., 2008). Power laws exhibit *scale invariance*, meaning that increasing r increases $p(r)$ by $r^{-\beta}$. Thus when the relationship between objects is described by a power law, the relationship remains similar regardless of the size of the objects. This effect is known as power law *scaling*. Equation 4 can be transformed into:

$$\log p(r) = \log G - \beta \log r \tag{5}$$

which allows for simple estimation using linear regression. To further explain the use of power laws in describing urban systems, we will review several recent works. We will then apply the above formulas to the set of centers produced in our analysis.

A.2 Literature Review

Recent work by Geoffrey West, such as "Urban Scaling and its Deviations" (Bettencourt et al., 2010), has driven new interest in the use of power law scaling to study urban distributions. Bettencourt, Lobo, Strumsky, and West used power laws to compare income, crime rates, and patent production between cities based on population size. They found that larger cities tend to have higher incomes, patent production, and crime rates than average. These quantities scale super-linearly, each with similar exponents (around 1.15). This is not a new concept on its own, but the authors discovered a far more interesting pattern by analyzing the deviations from the power scaling law. They found that deviations from the power law by individual cities remained remarkably consistent over time. Cities such as McAllen, Texas that underperformed expectations of income and innovation tended to consistently underperform at a similar level. Further, cities such as San Francisco that out performed expectations for income and innovation consistently outperformed expectations for decades. The authors categorized cities by their deviations, creating clusters of cities with similar histories. For example, high-tech centers such as San Francisco, San Jose, Minneapolis, Denver, and Seattle each had similar deviations, as did older industrial cities near transportation hubs, such as Pittsburgh, Cincinnati, Memphis, and Birmingham. This application of power law scaling illustrates how the history and structure of cities shapes their future consistently. Their work has driven further research at smaller scales, both on a theoretical basis, as with Salingaros, and in detailed analysis, as with Batty.

Nikos Salingaros, a mathematician and colleague of Christopher Alexander, provides a theoretical connection between the concept of urban centrality and recent empirical studies of scaling laws in cities. Alexander proposed the urban growth should be guided to produce a hierarchy of centers, such that every new increment of development generates at least one center at a larger scale, other centers at the same scale, and more centers at a smaller scale. This rule produces a distribution of few small elements and many larger elements, much like a power law. In *Principles of Urban Structure* (Salingaros et al., 2005), Salingaros describes Alexander's distribution using his model of the urban web. The web consists of nodes and connections set in a hierarchy. A node is a place of human activity and interconnectedness in the web. A connection is a link between nodes. These paths and nodes generate a self-organizing hierarchy. Salingaros suggests, much as Alexander did in "The City is Not a Tree" (Alexander, 1965), that paths should be designed to connect nodes of human activity in multiple ways, rather than collapsing multiple paths into single channels. Thus Salingaros's urban web is not a strict, tree-like hierarchy. Rather, it is web-like (as its name suggests) and is similar to the concept of the semi-lattice described in Alexander's 1965 work.

Salingaros then connects his concept of the urban web to power law scaling. The concept of scaling is significant because it is fundamental to how people perceive the city. "Scales play a major, even if subconscious, role in design because they facilitate the process of human cognition....If the distribution of scales and the relative multiplicity of elements correspond to an experientially generated internal standard, we perceive the structure as coherent.... Just as in music, we enjoy a building or city because it offers a mixture of regularity and surprise in a certain ratio." Salingaros proposes that power laws could define an optimal distribution for design elements, noting that West and Shlesinger argue that it is a "universal rule for both natural and man-made structures" (West and Shlesinger, 1990).

Unlike the field equations of basic physics used to describe electromagnetism, gravity and other fundamental forces, the structure of complex urban systems cannot be described deterministically. As Salingaros notes, "We cannot expect to describe a complex system by a field equation, because the mechanisms in complex systems are correlational rather than causal." Indeed, urban structure is subject to many different forces and attempts to describe it deterministically will fail. Salingaros elaborates that "the idea of causality is here replaced by the notion of concurrence, and the predictive relationships of physics are replaced by scaling relationships. Therefore, a scaling rule for complex systems is just as basic an organizing principle as an analytic law in physics. A field equation is usually stated in terms of analytic functions that obey an equation of motion. In a complex system, on the other hand, the best description is in terms of probability distributions." Thus scaling laws are a useful tool for discovering the underlying structure of the city. Scaling laws provide a predictive model for how the city develops and helps reveal the mechanisms controlling urban form.

In "Scaling and Allometry in the Building Geometries of Greater London" (Batty et al., 2008), Batty and his coauthors note that an extensive number of studies compare the rank-size scaling of set of cities, but relatively little work studies the scaling within cities, though a similar pattern is plainly visible. Their article attempts to extend such studies to the spatial structure of the city itself. Further, they extend their analysis by examining how the spatial constraints of geometry affect the scaling distributions. The authors estimate a power law scaling model for a large data set containing building heights for all of London and also smaller data sets of large world buildings, large New York buildings, and large Tokyo buildings. For the set of London buildings, the authors estimate beta, the inverse power, and alpha, the power, for several geometric types. For each set, they perform a linear regression on the top 10 percent of buildings, using their assumption that the power law approximates the log-normal on its fat tail. They find an alpha value of 2.3 for scaling on building area and an alpha value of 2.2 for scaling on building volume.

Other studies have extended the use of power laws to describe other aspects of urban behavior. In Roth et al. (2011), the authors use power law scaling and theories of centrality to describe travel patterns on the London subway system. Using data from the Oyster card databases, they found that movement within London is highly polycentric, with most trips originating from locations throughout and ending at several dense centers in central London. Similarly, Samaniego (2008) applied metabolic scaling theory, as described by Geoffrey West and others to the study of the urban road network. In much the same way that the structure of an organism's vascular network is a constraint on that organism's allometry (that is, the organism's form described by the relationship of volume, surface area, and geometry), a city's road network is a constraint on its development. The authors modeled two idealized relationships between a city's area and its road area: one describing a city in which all travel is completely centralized, traveling only to the city's center, and the other describing a city with completely decentralized travel patterns, with all travel going to the nearest destination. They then compared the form of 425 US urban areas to these idealized relationships and discovered that most cities were built as though travel was completely decentralized. Further study showed that actual travel patterns lie closer to the centralized model.

It is clear that scaling laws provide a useful method for describing the relationships between empirical measures of urban form. As Batty et. al note, "Cities. . . are composed of fractal-like clusters on many spatial scales whose order appears to follow well-defined numerical rules of scaling." In other words, past work on the scaling between cities as a whole has not fully described the scaling relationships present within cities themselves. The urban network is composed of centers all the way down, from the scale of megacities to the scale of sidewalk cafs. Power laws provide, as Salingaros put it, a basic organizing principle for describing complex urban systems.

A.3 Analysis

In the primary analysis of thesis thesis, we produced a set of centers describing the distribution of commercial intensity in Atlanta. We will now apply the methods used in Batty et al. (2008) to determine whether our data fits a power law. Batty notes that "the current conventional wisdom is that the power law is a good approximation to the description of the log-normal in its 'fat tail' which describes the form of the largest sizes in the distribution." Thus they derive an equation for density as a function of rank that can be easily estimated using a linear regression model to estimate beta, the inverse power of the power scaling law derived from the data. This is equation 5 above.

We analyzed our set of centers for each bandwidth and dependent variable ($EstSqFt\_Sum$, KD_Volume, and KD_Max). We normalized our data using Batty's methods, dividing the dependent variable by its mean, and dividing the rank of each center by the maximum rank. Plotting these on a *log-log* graph, as in Figure 46, reveals a log-normal distribution similar to Batty's distribution of building sizes in world cities. Using the top ten percent of each set of centers by rank allows us to use equation 5 to estimate β with a linear regression. The results of this analysis are summarized in Table 8, with one model plotted in Figure 46.

Each of the three dependent variables produces similar results. For bandwidths less than 4.0 miles, each R^2 is close to one and statistically significant. The β values fall in a range from 0.52 to 0.74. These values are much smaller than the β of 1.0 predicted by Zipf's law for city size, but they are in a similar range to Batty's results. Using the database of London buildings, he found a β of 0.76 for building area, a β value of 0.46 for building height, and a β of 0.86 for building volume. Because our R^2 values are quite high, and because our β values fall in a similar range to the results in Batty et al. (2008), we conclude that the distribution of commercial centers in Atlanta scales according to a power law.

Table 8: Results of linear regressions using equation 5 to estimate the fit of a power law. For each regression, only the top ten percent of centers by rank were analyzed. The resulting β values are similar to those found in Batty's analysis of London buildings (Batty et al., 2008).

		0.125	0.25	0.5	1	2	4
$EstSqFt\_Sum$	R^2	0.99**	0.99**	0.98**	0.97**	0.95**	0.85*
	β	0.548	0.579	0.645	0.735	0.691	0.354
KD_Volume	R^2	0.99**	0.99**	0.99**	0.98**	0.95**	0.87*
	β	0.545	0.579	0.645	0.739	0.697	0.371
KD_Max	R^2	1.00**	0.99**	0.99**	0.99**	0.92**	0.98**
	β	0.533	0.523	0.544	0.604	0.655	0.303

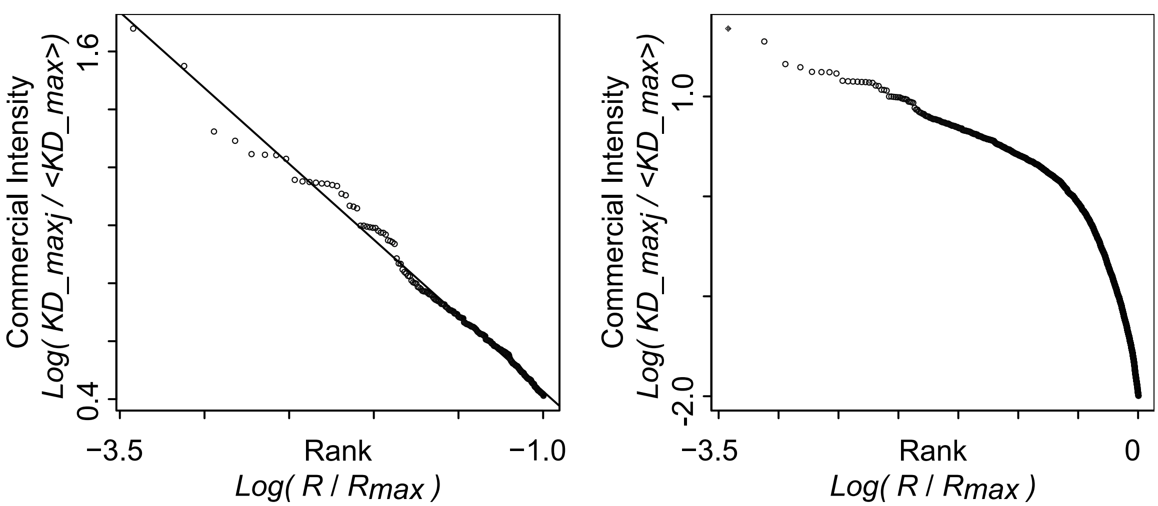

Figure 46: Plot of the normalized rank (x axis) versus the normalized commercial intensity (y axis). Here, the commercial intensity measure is the maximum value of the kernel density estimation at each center (KD_Max), and the centers used are the set of 0.25 mile bandwidth centers. The Figure on the left represents the top ten percent of centers by commercial intensity. Batty et al. (2008) indicate that "the power law is a good approximation to the distribution of the log-normal in its fat tail which describes the form of the largest sizes in the distribution." Thus a model fit to the top ten percent of the centers is a good approximation for measuring the power law describing the distribution.

APPENDIX B

FURTHER QUANTITATIVE ANALYSIS

B.1 Additional Regression Tables

The following tables display the results of the linear regressions described in section 4.4. While the tables in section 4.4 were limited to the 0.50 mile, 1.0 mile, and 4.0 mile bandwidths, these Table include all seven bandwidths analyzed. They are included here for reference.

Table 9: Results of linear regression analyses for each directional reach measure and every bandwidth. R^2 is the correlation coefficient, B is the slope derived from the regression, and the statistical significance, P, of each regression is indicated by: ** $P < 0.01$; * $P < 0.05$.

		Bandwidth						
		0.125	0.25	0.5	1	2	4	8
$ln(DR0A\_max)$	R^2	0.088**	0.133**	0.202**	0.273**	0.341*	0.468	0.235
	B	0.437	0.668	0.992	1.342	1.615	2.305	1.794
$ln(DR0L\_max)$	R^2	0.041**	0.057**	0.083**	0.098**	0.137**	0.317**	0.345
	B	0.359	0.562	0.889	1.163	1.574	3.056	2.484
$ln(DR2A\_max)$	R^2	0.129**	0.224**	0.315**	0.380**	0.430**	0.531**	0.467*
	B	0.415	0.681	0.962	1.191	1.361	1.904	1.613
$ln(DR2L\_max)$	R^2	0.050**	0.096**	0.147**	0.190**	0.246**	0.348**	0.441
	B	0.326	0.583	0.907	1.188	1.462	2.215	1.439

Table 10: Results of linear regression analyses for each metric reach measure and every bandwidth. R^2 is the correlation coefficient, B is the slope derived from the regression, and the statistical significance, P, of each regression is indicated by: ** $P < 0.01$; * $P < 0.05$.

		Bandwidth						
		0.125	0.25	0.5	1	2	4	8
$ln(MR025L\_mean)$	R^2	0.047**	0.100**	0.274**	0.446**	0.622**	0.66**1	0.80**0
	B	1.133	1.965	4.884	7.597	10.30	11.64	10.66
$ln(MR050L\_mean)$	R^2	0.062**	0.139**	0.289**	0.466**	0.644**	0.702**	0.797**
	B	1.049	1.944	3.531	5.227	6.928	7.803	6.954
$ln(MR100L\_mean)$	R^2	0.131**	0.221**	0.365**	0.511**	0.683**	0.747**	0.829**
	B	1.305	1.943	2.972	3.884	4.954	5.486	4.811
$ln(MR100A\_mean)$	R^2	0.093**	0.174**	0.322**	0.489**	0.673**	0.745**	0.813**
	B	1.124	1.782	2.909	3.999	5.159	5.735	5.013
$ln(MR500A\_mean)$	R^2	0.156**	0.222**	0.325**	0.462**	0.637**	0.721**	0.911**
	B	1.389	1.774	2.304	2.753	3.222	3.058	3.349

Table 11: Results of linear regression analyses for each directional reach measure and every bandwidth, limited to those centers falling within the City of Atlanta. R^2 is the correlation coefficient, B is the slope derived from the regression, and the statistical significance, P, of each regression is indicated by: ** $P < 0.01$; * $P < 0.05$

		Bandwidth and Neighborhood Scale				
		0.125	0.25	0.5	1	2
$ln(DR0A\_max)$	R^2	0.079**	0.118**	0.124**	0.416**	0.233
	B	0.581	0.791	1.115	2.251	1.148
$ln(DR0L\_max)$	R^2	0.044**	0.046**	0.053*	0.367**	0.882*
	B	0.472	0.567	0.874	2.605	3.885
$ln(DR2A\_max)$	R^2	0.071**	0.194**	0.199**	0.611**	0.363
	B	0.411	0.780	0.989	1.829	1.382
$ln(DR2L\_max)$	R^2	0.024**	0.087**	0.118**	0.539**	0.721
	B	0.240	0.546	0.832	1.985	2.589

Table 12: Results of linear regression analyses for each metric reach measure and every bandwidth, limited to those centers falling within the City of Atlanta. R^2 is the correlation coefficient, B is the slope derived from the regression, and the statistical significance, P, of each regression is indicated by: ** $P < 0.01$; * $P < 0.05$

		Bandwidth and Neighborhood Scale				
		0.125	0.25	0.5	1	2
$ln(MR025L\_mean)$	R^2	0.002**	0.055**	0.205**	0.407**	0.438**
	B	0.208	1.245	2.993	5.715	4.533
$ln(MR050L\_mean)$	R^2	0.006**	0.067**	0.206**	0.482**	0.476**
	B	0.307	1.097	2.359	4.699	3.789
$ln(MR100L\_mean)$	R^2	0.047**	0.171**	0.290**	0.599**	0.500**
	B	0.823	1.700	2.516	4.208	3.877
$ln(MR100A\_mean)$	R^2	0.014**	0.085**	0.209**	0.542**	0.556**
	B	0.440	1.186	2.165	4.249	3.974
$ln(MR500A\_mean)$	R^2	0.009**	0.063**	0.182**	0.471**	0.680**
	B	0.727	1.964	3.281	5.205	6.303

B.2 Neighborhood Scale Analysis

The previous analysis, in section 4.4, allowed us to measure the correlation between commercial intensity and urban form using centers derived from a kernel density estimation (KDE) raster at various bandwidths. This essentially allowed us to measure the different patterns of commercial centrality for commercial activities at different scales – from the very small scale of a neighborhood grocer to the very large scale of regional shopping centers. However, this analysis does not allow us to analyze the difference in correlation between large centers or small centers at the same bandwidth. If we wanted to know whether the largest small bandwidth centers interacted with form differently from the smallest small bandwidth centers, we would need another method.

Table 13: Count of centers by bandwidth and neighborhood scale

	Neighborhood Scale								
Bandwidth	0.125	0.25	0.5	1	2	4	8	16	Total
0.125	745	2324	966	509	178	50	15	1	4788
0.25	175	1216	767	443	164	47	14	1	2827
0.5	65	365	484	333	139	49	13	1	1449
1	12	112	136	204	103	44	12	1	624
2	5	15	27	54	63	29	10	1	204
4	2	4	4	13	11	14	9	1	58
8			1		1	4	2	1	9
16								1	1
Total	1004	4036	2385	1556	659	237	75	8	9960

To accomplish this analysis, we use the set of centers for each bandwidth stratified by neighborhood scale as described in 3.3.2. We further stratified the point centers of each bandwidth into scales, recognizing which point centers are largest over a given radius. Rather than using our 375 m neighborhood radius, we measure which centers are local maxima over radii of 0.125 miles to 16.0 miles in the same sequence as above. Thus we are able to determine which point centers on the 2.0 mile bandwidth KDE raster are maxima over a 1.0 mile radius, and which are maxima over only a 0.25 mile radius. The two methods for calculating these centers describe different methods for measuring the impact of commercial activity over space. The categorization by bandwidth and neighborhood scale is described in Table 13. We repeat our previous analysis, performing a linear regression for each combination of independent and dependent variables, and for the four methods for taking natural logarithms of the variables.

Table 14: Results of linear regression analyses for each directional reach measure and bandwidth using only centers with a minimum neighborhood scale of the bandwidth. R^2 is the correlation coefficient, B is the slope derived from the regression, and the statistical significance, P, of each regression is indicated by: ** $P < 0.01$; * $P < 0.05$

		Bandwidth and Neighborhood Scale					
		0.125	0.25	0.5	1	2	4
$ln(DR0A\_max)$	R^2	0.09**	0.13**	0.22**	0.28**	0.34**	0.24*
	B	0.44	0.67	1.05	1.28	1.65	1.72
$ln(DR0L\_max)$	R^2	0.04**	0.06**	0.07**	0.08**	0.08**	0.32**
	B	0.36	0.56	0.84	1.05	1.35	2.87
$ln(DR2A\_max)$	R^2	0.13**	0.23**	0.34**	0.40**	0.41**	0.44**
	B	0.41	0.69	1.00	1.18	1.41	1.94
$ln(DR2L\_max)$	R^2	0.05**	0.10**	0.15**	0.18**	0.17**	0.48**
	B	0.33	0.59	0.89	1.12	1.32	2.55

Table 15: Results of linear regression analyses for each metric reach measure and bandwidth using only centers with a minimum neighborhood scale of the bandwidth. R^2 is the correlation coefficient, B is the slope derived from the regression, and the statistical significance, P, of each regression is indicated by: ** $P < 0.01$; * $P < 0.05$

		Bandwidth and Neighborhood Scale					
		0.125	0.25	0.5	1	2	4
$ln(MR025L\_mean)$	R^2	0.05**	0.14**	0.33**	0.50**	0.64**	0.38**
	B	1.13	2.65	5.38	7.36	10.12	7.67
$ln(MR050L\_mean)$	R^2	0.06**	0.15**	0.35**	0.53**	0.67**	0.44**
	B	1.05	2.05	3.89	5.11	6.87	5.63
$ln(MR100L\_mean)$	R^2	0.09**	0.19**	0.40**	0.56**	0.71**	0.56**
	B	1.12	1.86	3.20	3.95	5.21	4.63
$ln(MR100A\_mean)$	R^2	0.13**	0.24**	0.45**	0.59**	0.72**	0.55**
	B	1.30	2.01	3.24	3.89	4.95	4.32
$ln(MR500A\_mean)$	R^2	0.16**	0.24**	0.44**	0.59**	0.77**	0.77**
	B	1.39	1.83	2.60	2.85	3.48	3.33

The results of this stratified analysis are in tables 14 and 15. The R^2 values show same pattern as the overall analysis, with an increase as bandwidth increase. The B values for each regression give an interesting illustration of the difference between each method of measuring reach. For the directional reach variables, the analyses on non-freeway roads each have a lower slope and weaker correlation than the corresponding analysis on all roads, except for the 4.0 mile bandwidth. This suggests that centers at most scales of analysis follow the same freeway logic we noticed in the bandwidth-only analysis above. However, for large scales, local roads seem to have a higher importance.

Table 15 also reveals interesting patterns between metric reach variables. The variables calculated on local roads have larger slopes for all except the smallest bandwidths. Other than the 0.125 mile, and to a lesser extent the 0.25 mile bandwidths, analyses using reach on only the set of local roads have consistently higher slopes and similar correlations compared to analyses using reach on all roads. More so, the smaller the reach radius, the larger the slope in the analysis. This suggests that, for a given bandwidth, commercial activity is more strongly tied to the small scale density of the road network than it is to its overall position within the road network, that is, whether it is near another larger center or far from all centers. Put more simply, a center will be larger if it has a strong local road network than if it has strong connectivity on its periphery.

Together, the tables 14 and 15 reveal a key point about the logic of Atlanta's road network. For most scales of analysis, a strong local road network and a location on a long road connected to a freeway have the most impact on the size of a center. While the logic differs when the level of commercial activity considered is 0.25 miles or less or 4.0 miles or more, for most scales the pattern holds true.

APPENDIX C

ADDITIONAL DIAGRAMS

The following diagrams further explain the process of creating a set of centers from the SMARTRAQ data, as described in chapter 3. They are included here to prevent disrupting the flow of the text.

C.1 Three Dimensional Kernel Density Diagrams

The following series of diagrams illustrate the results of the kernel density estimation process described in section 3.3.1. Included here are diagrams illustrating bandwidths from 0.50 miles to 16.0 miles. The smaller bandwidths were too complex to provide a worthwhile illustration of the surface. These diagrams present a helpful illustration of the distribution of commercial intensity over the surface of the city.

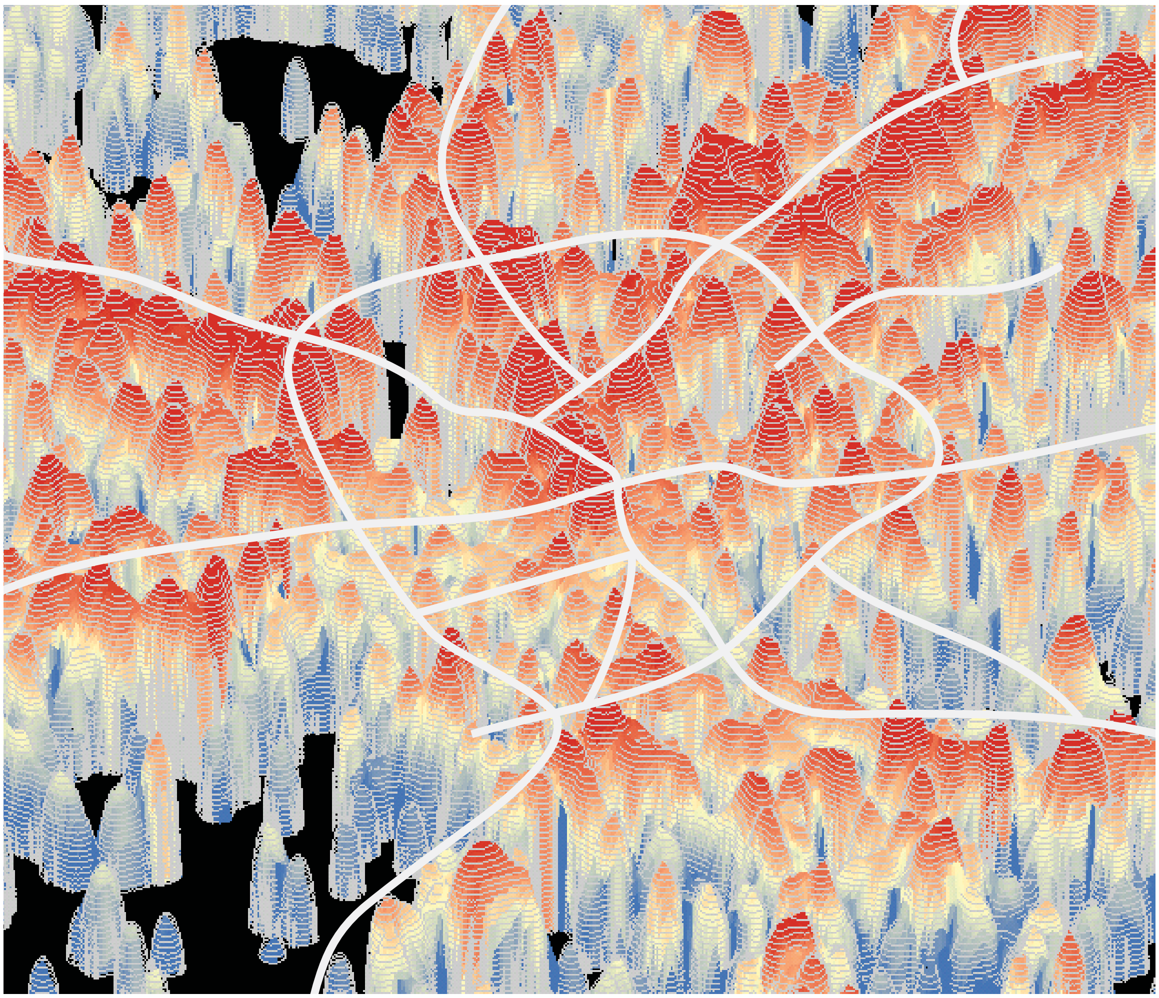

Figure 47: Three dimensional illustration of KDE, 0.50 mile bandwidth

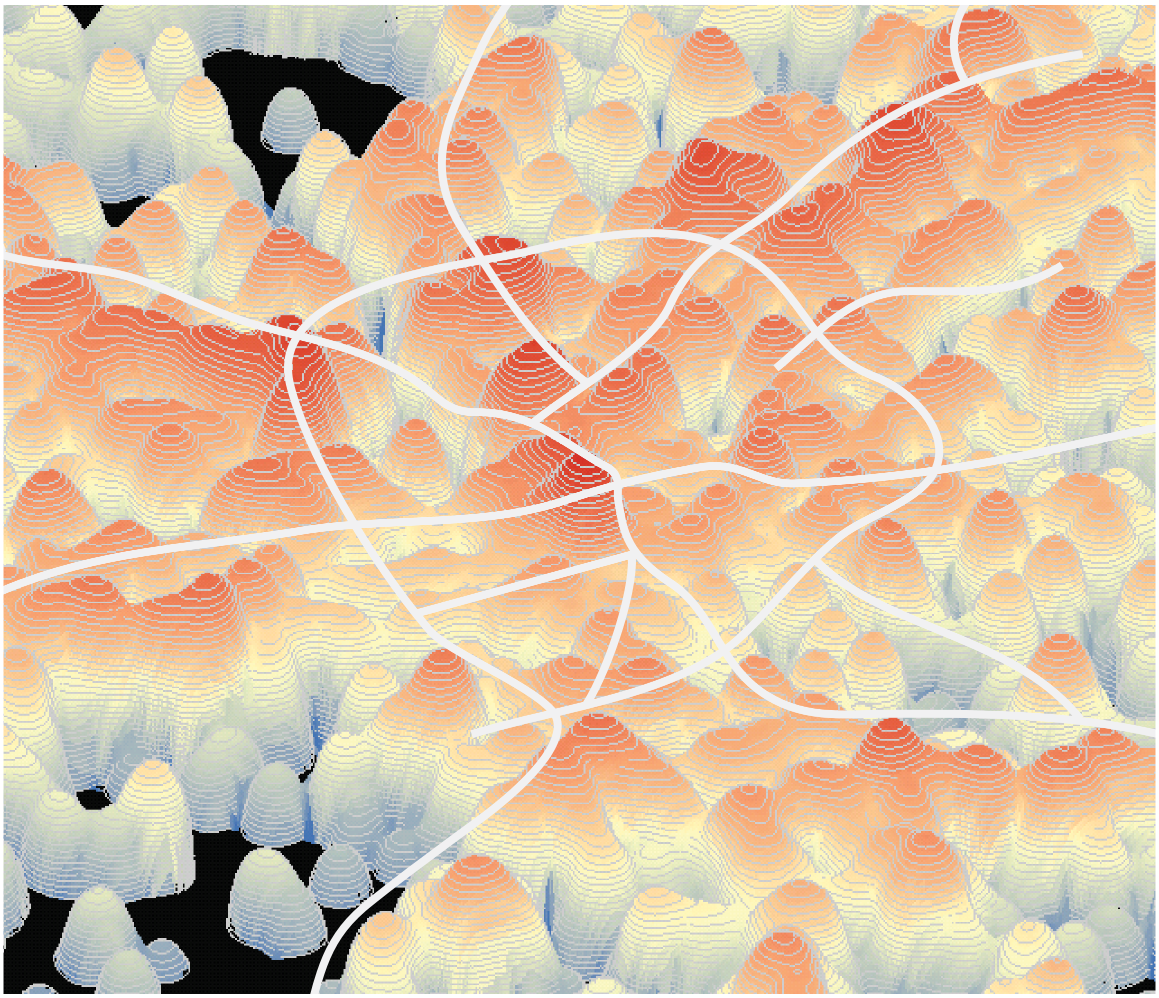

Figure 48: Three dimensional illustration of KDE, 1.0 mile bandwidth

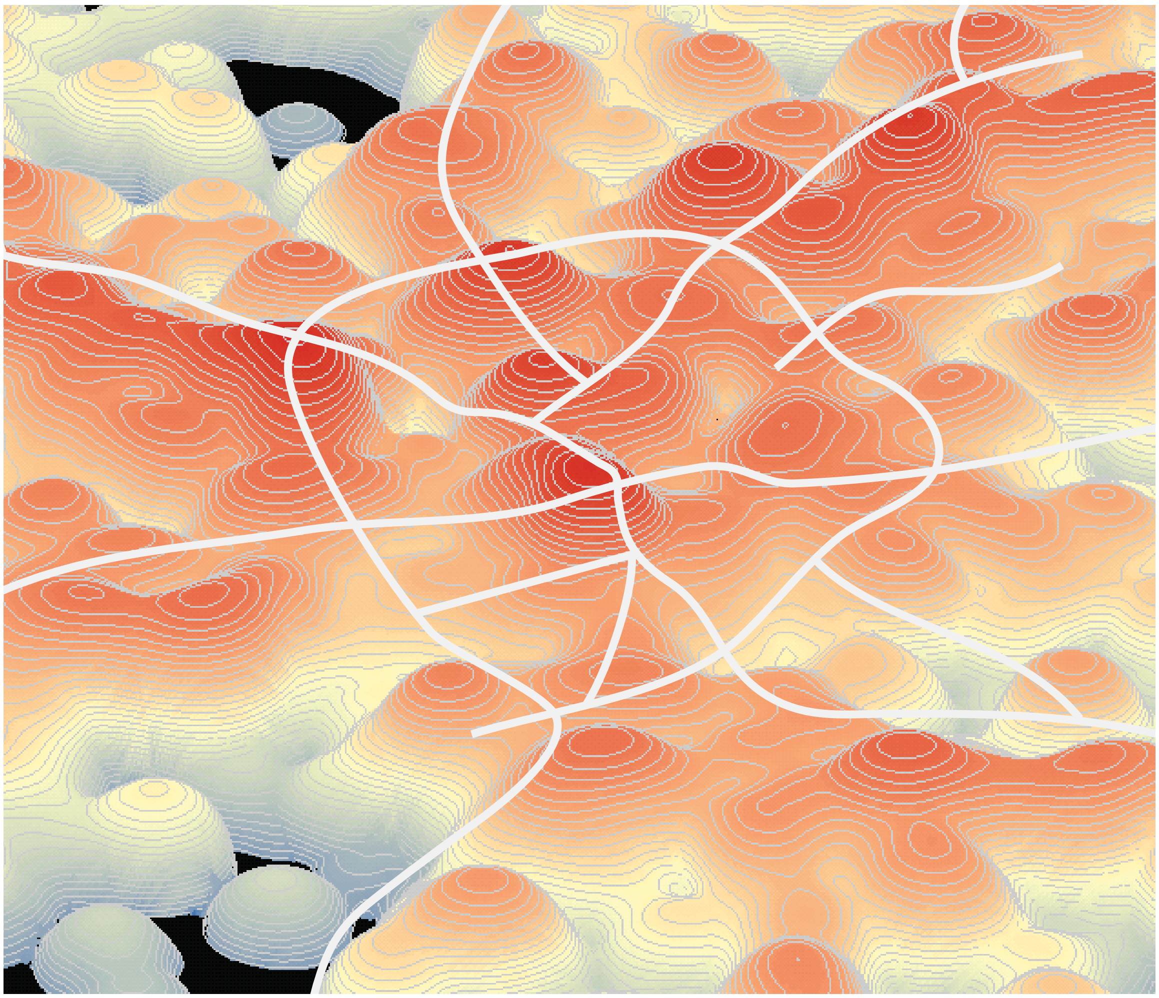

Figure 49: Three dimensional illustration of KDE, 2.0 mile bandwidth

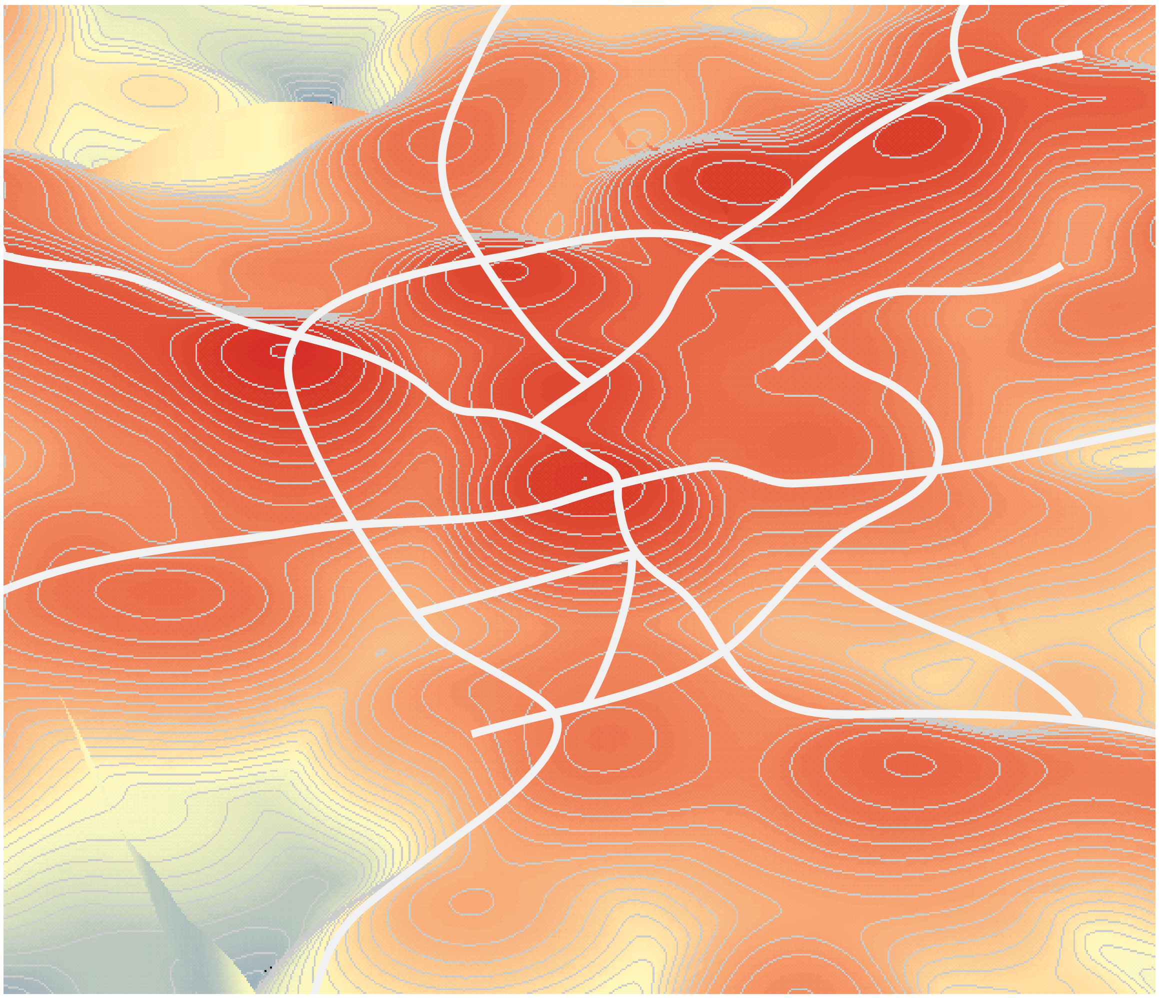

Figure 50: Three dimensional illustration of KDE, 4.0 mile bandwidth

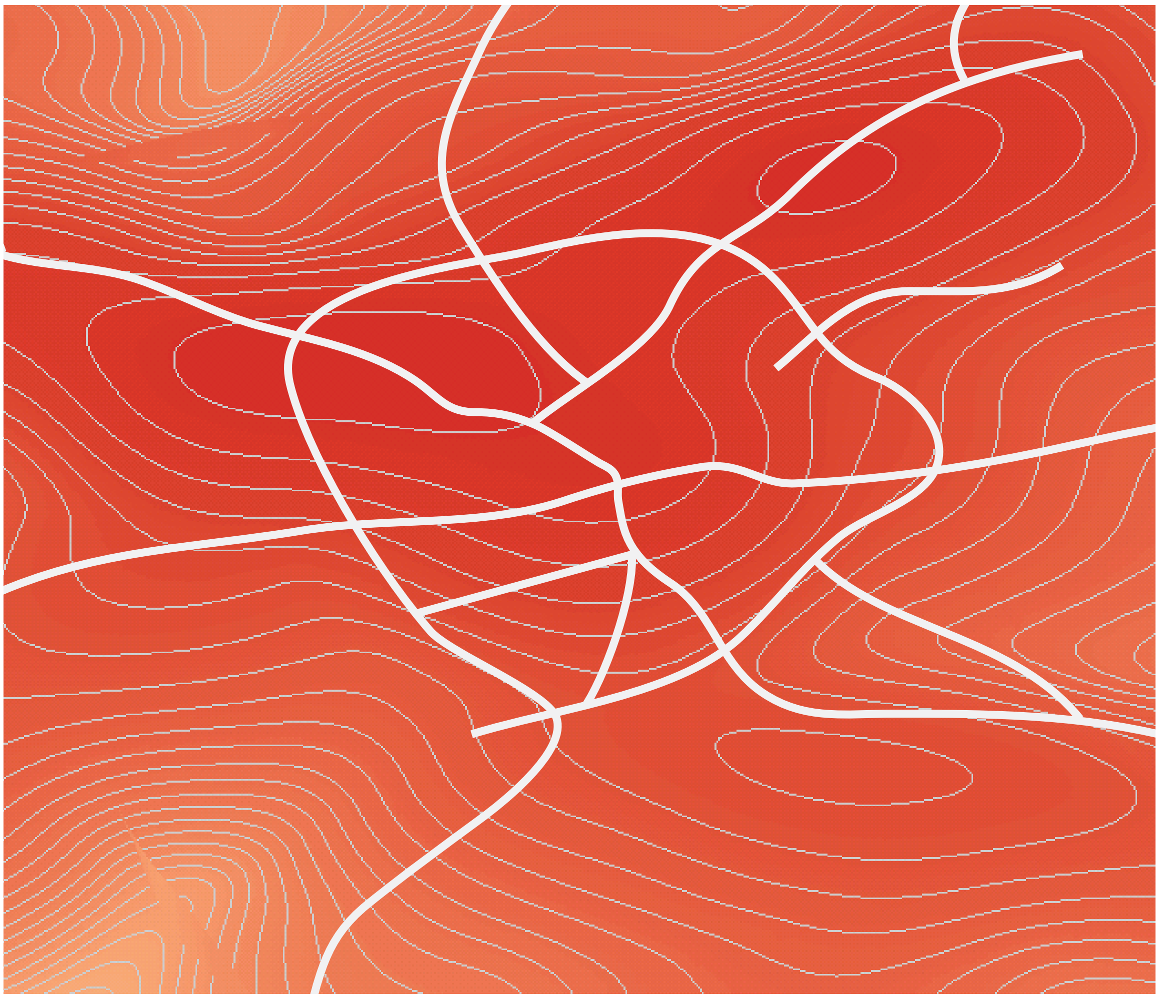

Figure 51: Three dimensional illustration of KDE, 8.0 mile bandwidth

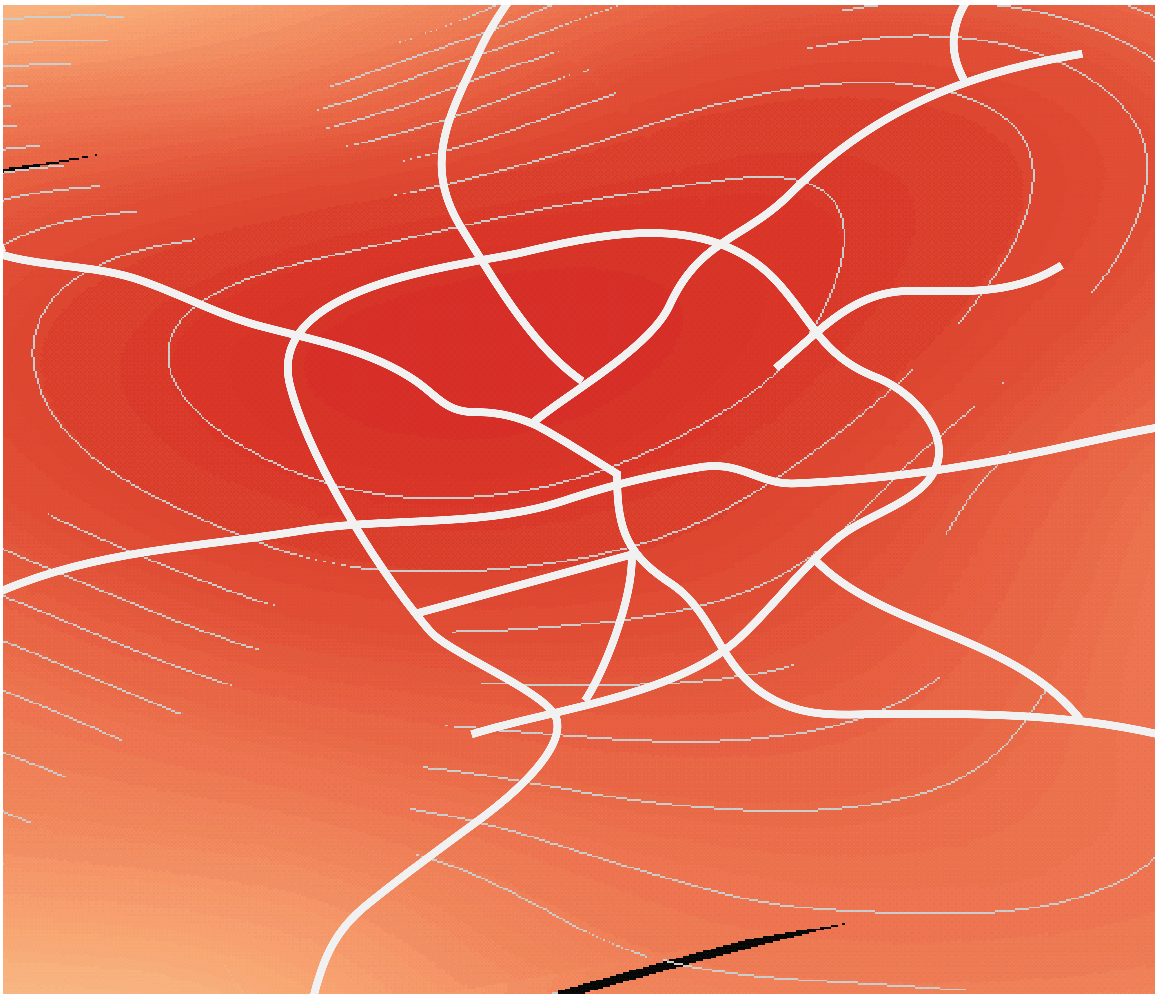

Figure 52: Three dimensional illustration of KDE, 16.0 mile bandwidth

C.2 Market Areas

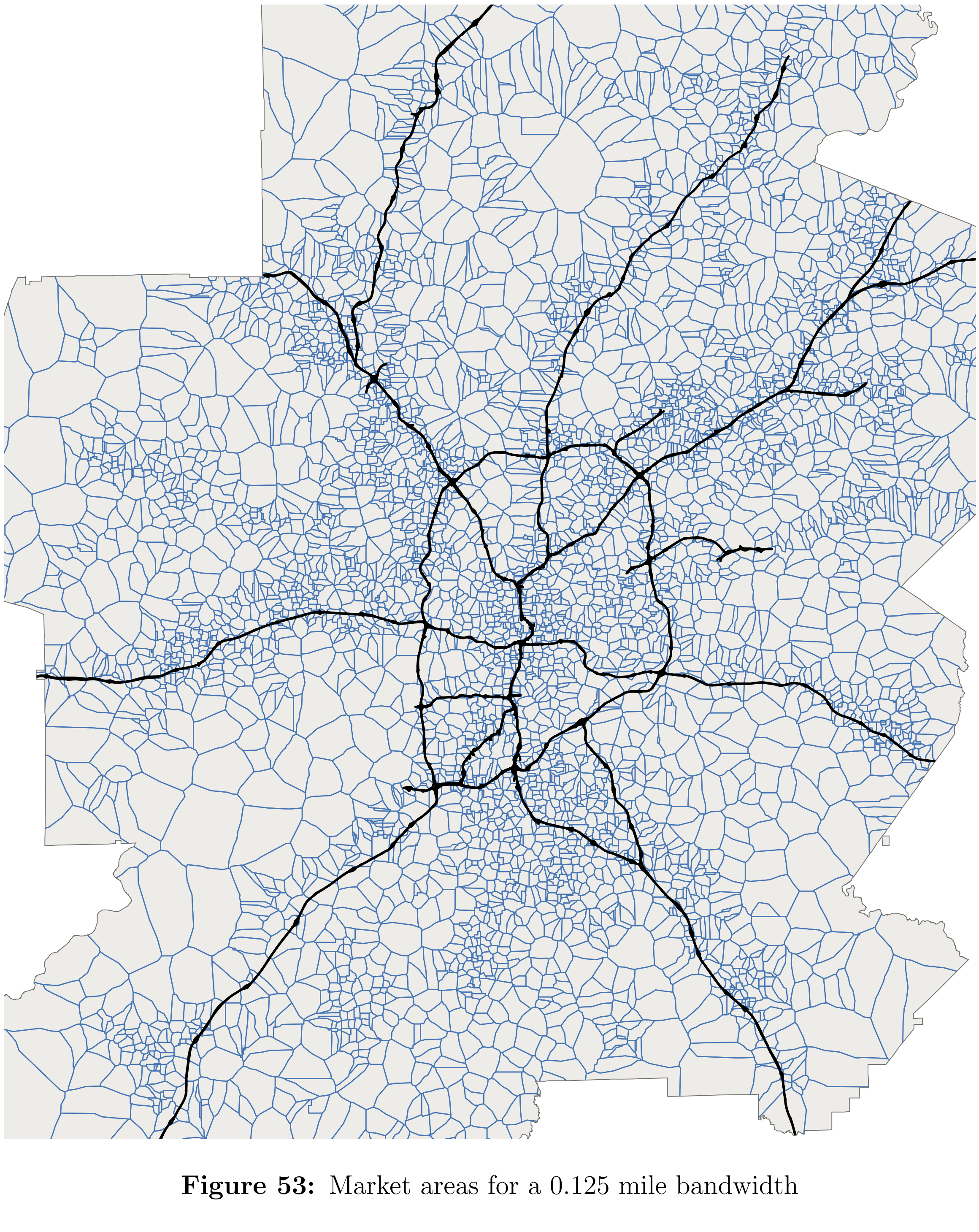

Figure 53: Market areas for a 0.125 mile bandwidth

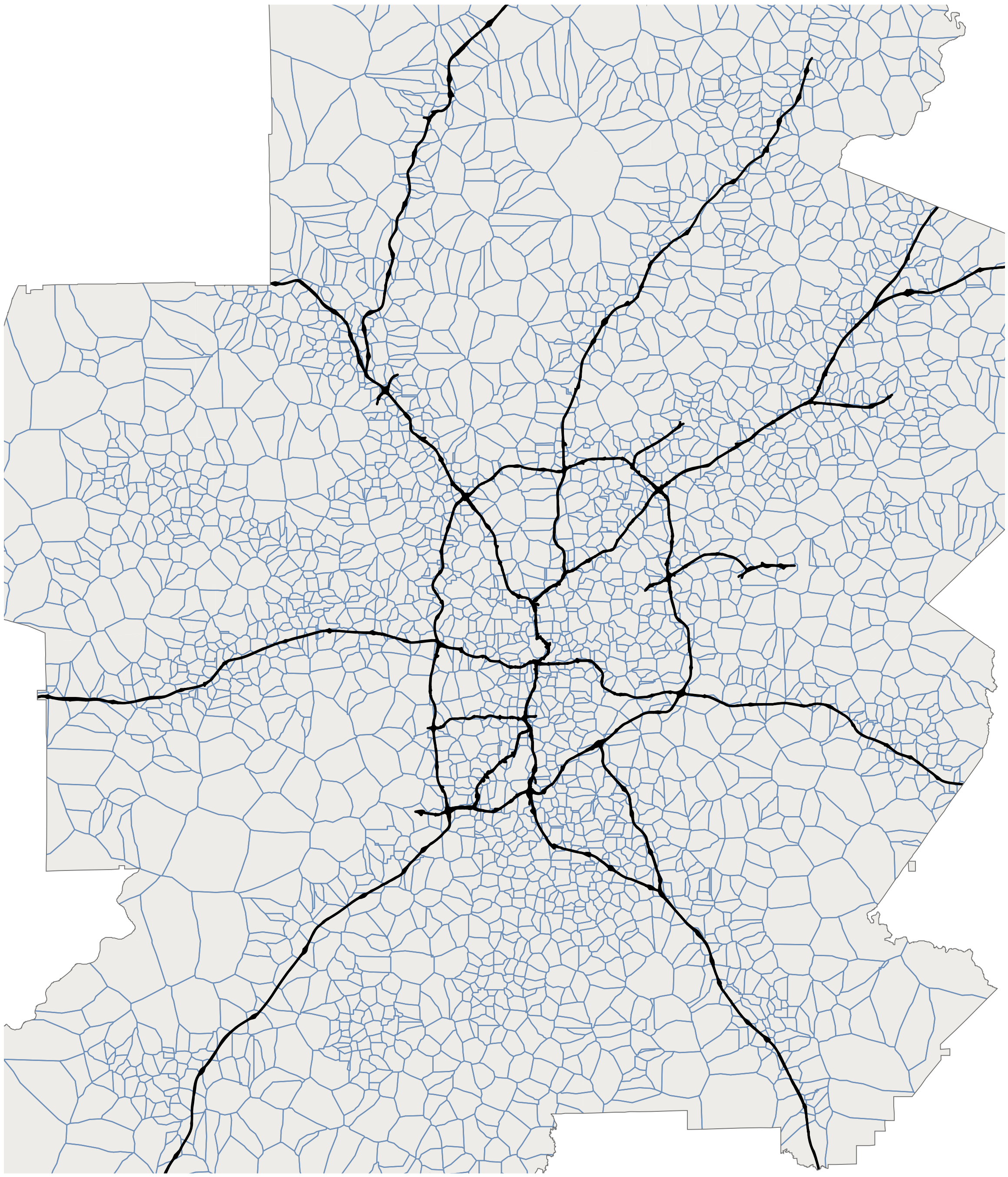

Figure 54: Market areas for a 0.25 mile bandwidth

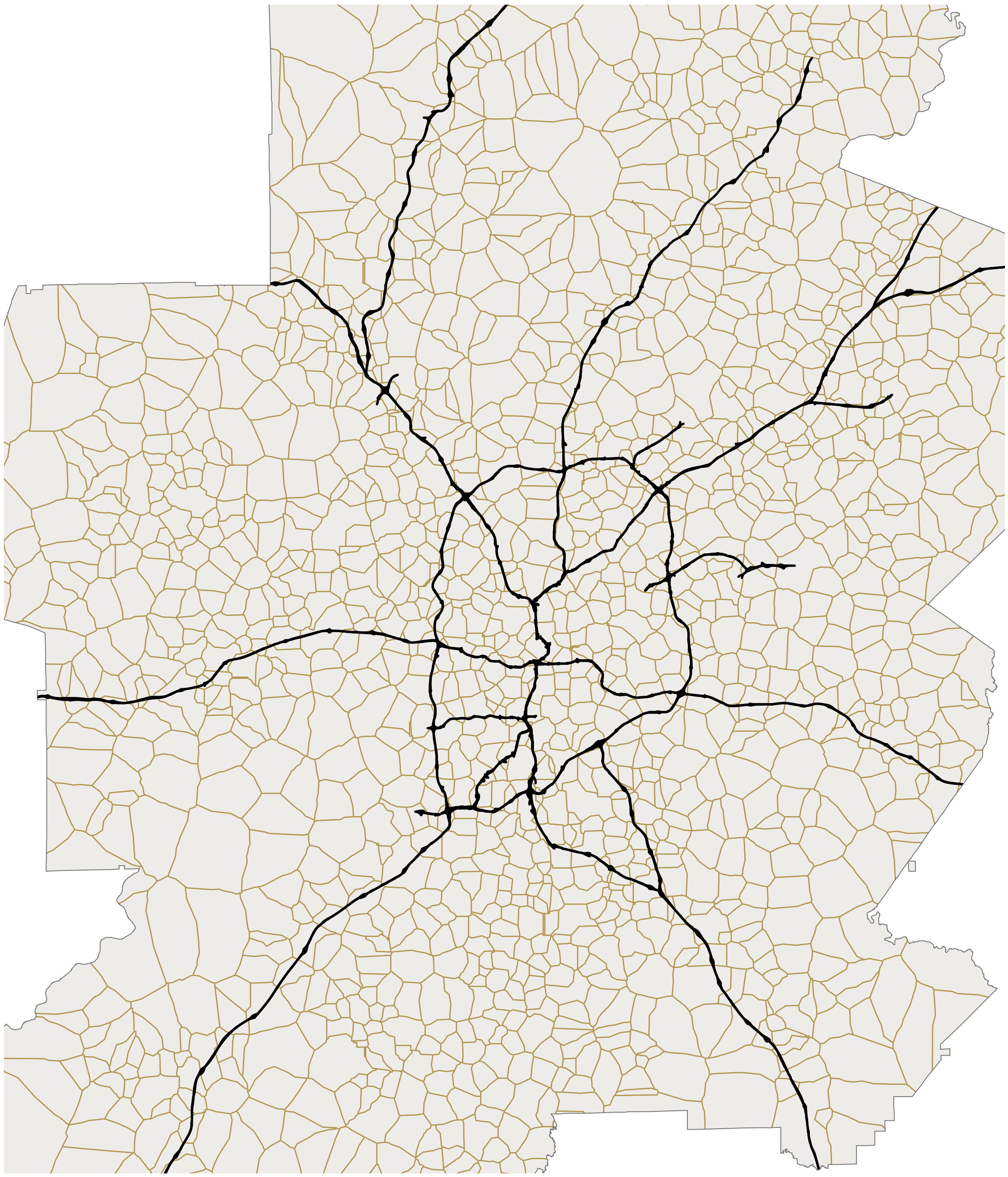

Figure 55: Market areas for a 0.50 mile bandwidth

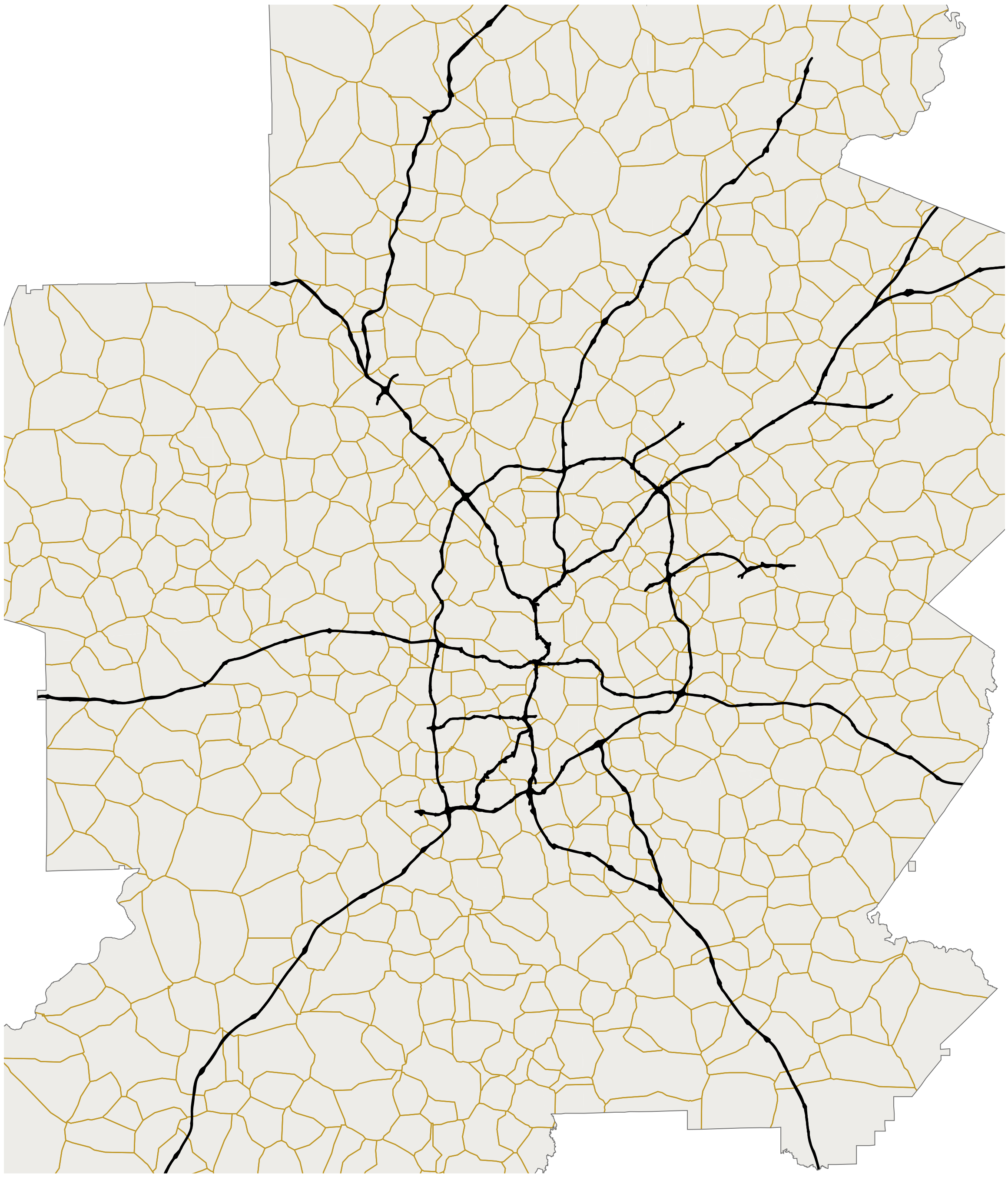

Figure 56: Market areas for a 1.0 mile bandwidth

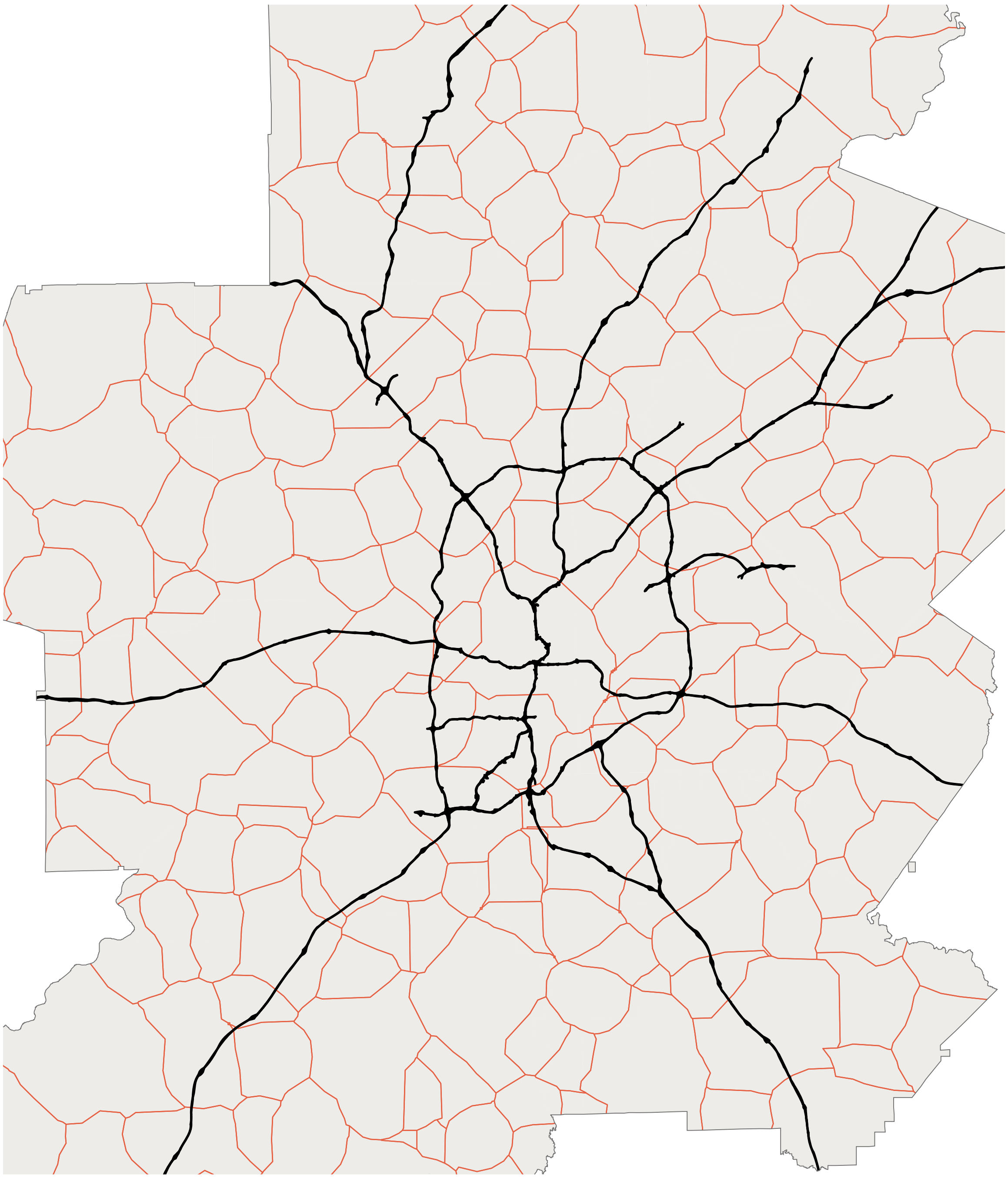

Figure 57: Market areas for a 2.0 mile bandwidth

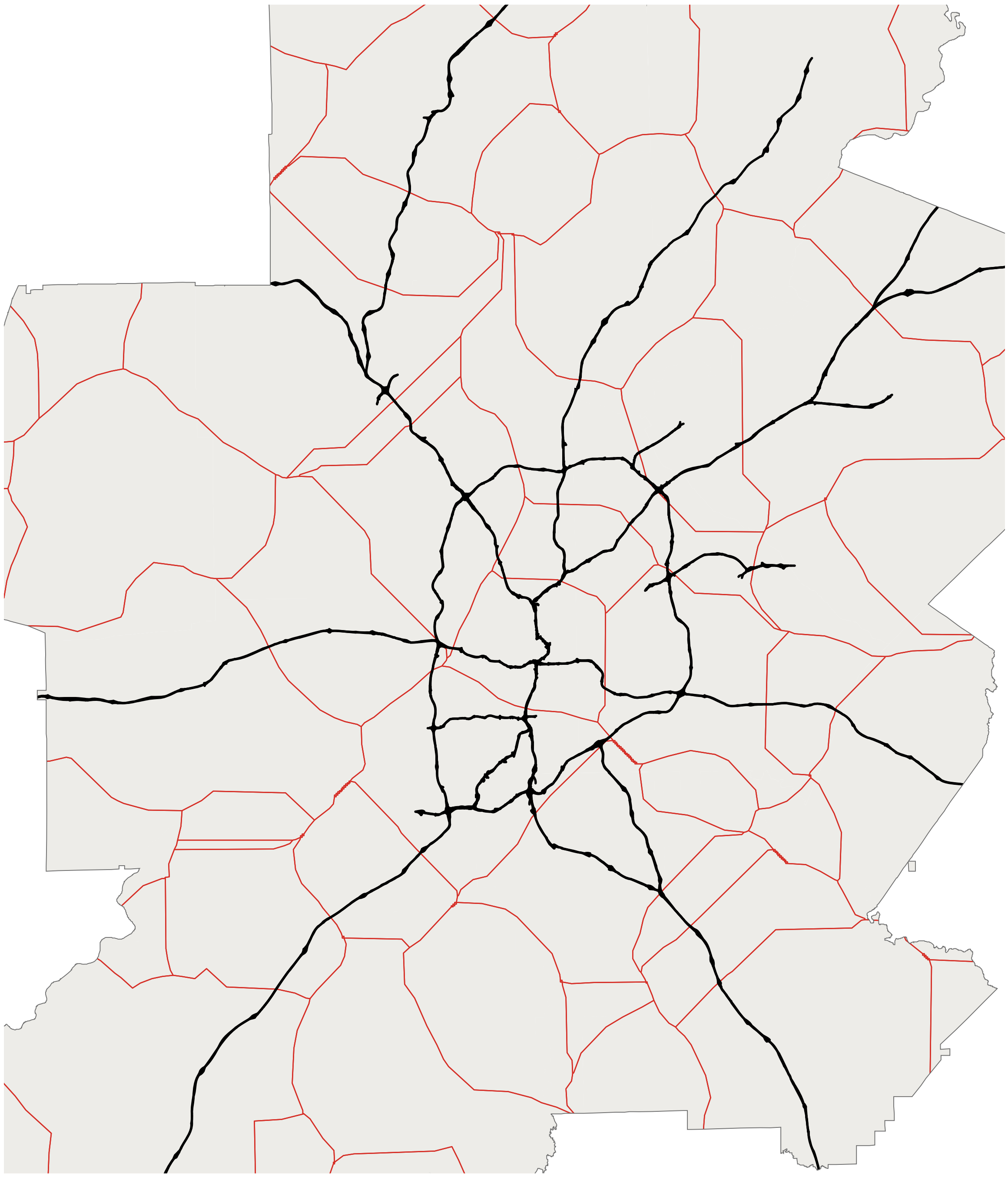

Figure 58: Market areas for a 4.0 mile bandwidth

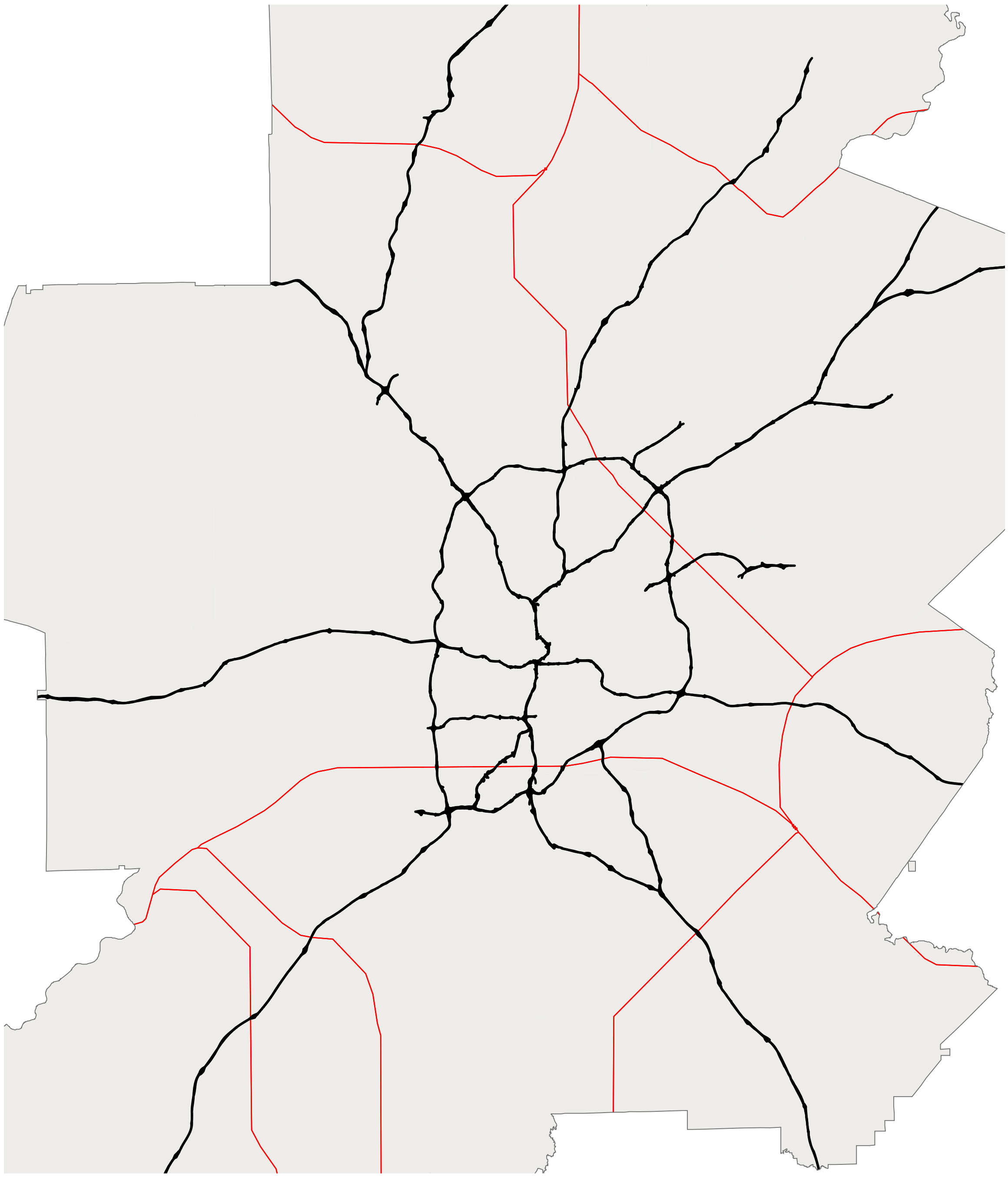

Figure 59: Market areas for a 8.0 mile bandwidth

C.3 Reach Measures

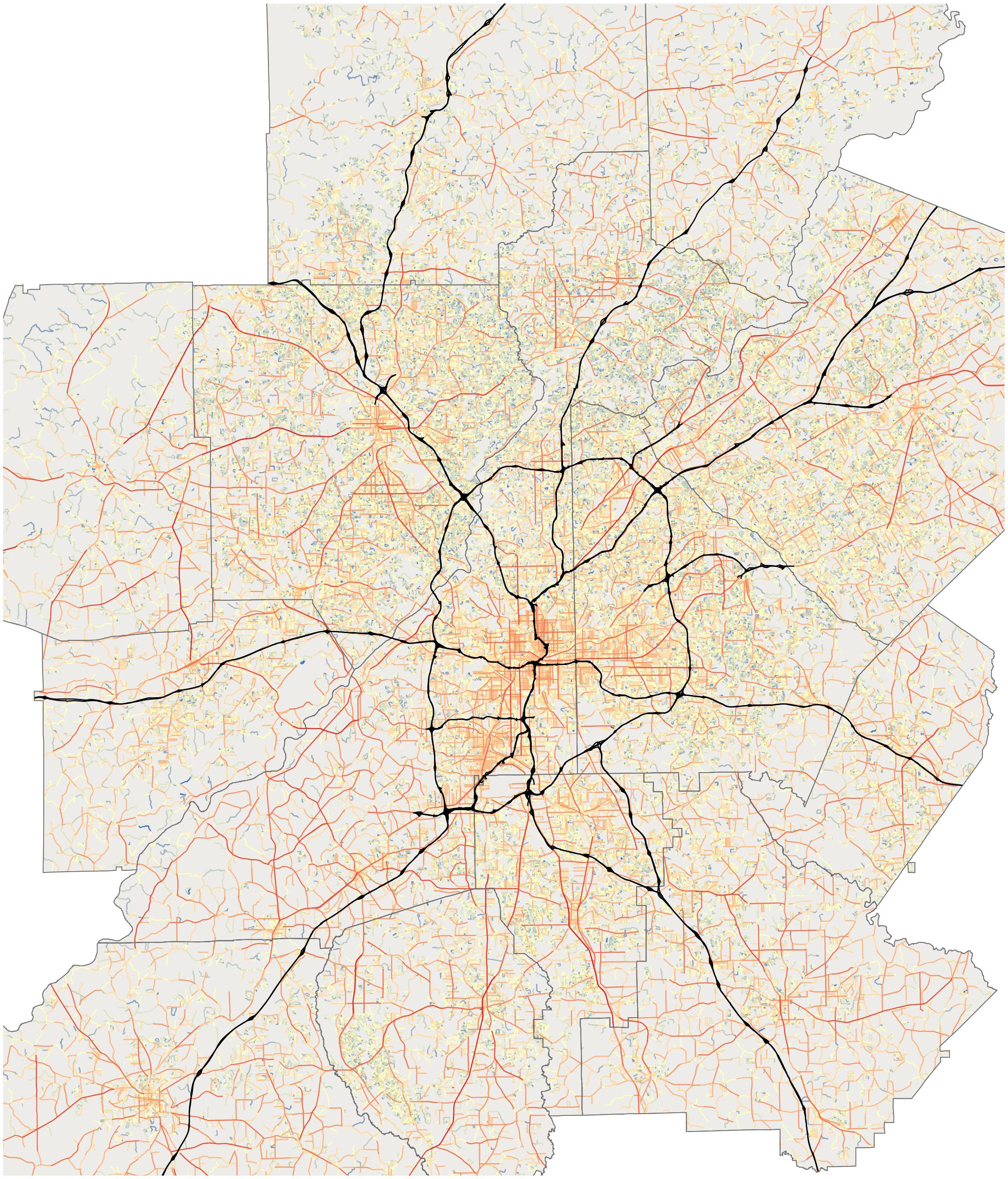

Figure 60: Diagram of directional reach with zero turns on non-freeway roads. Blue roads have the lowest reach value, and red roads have the highest.

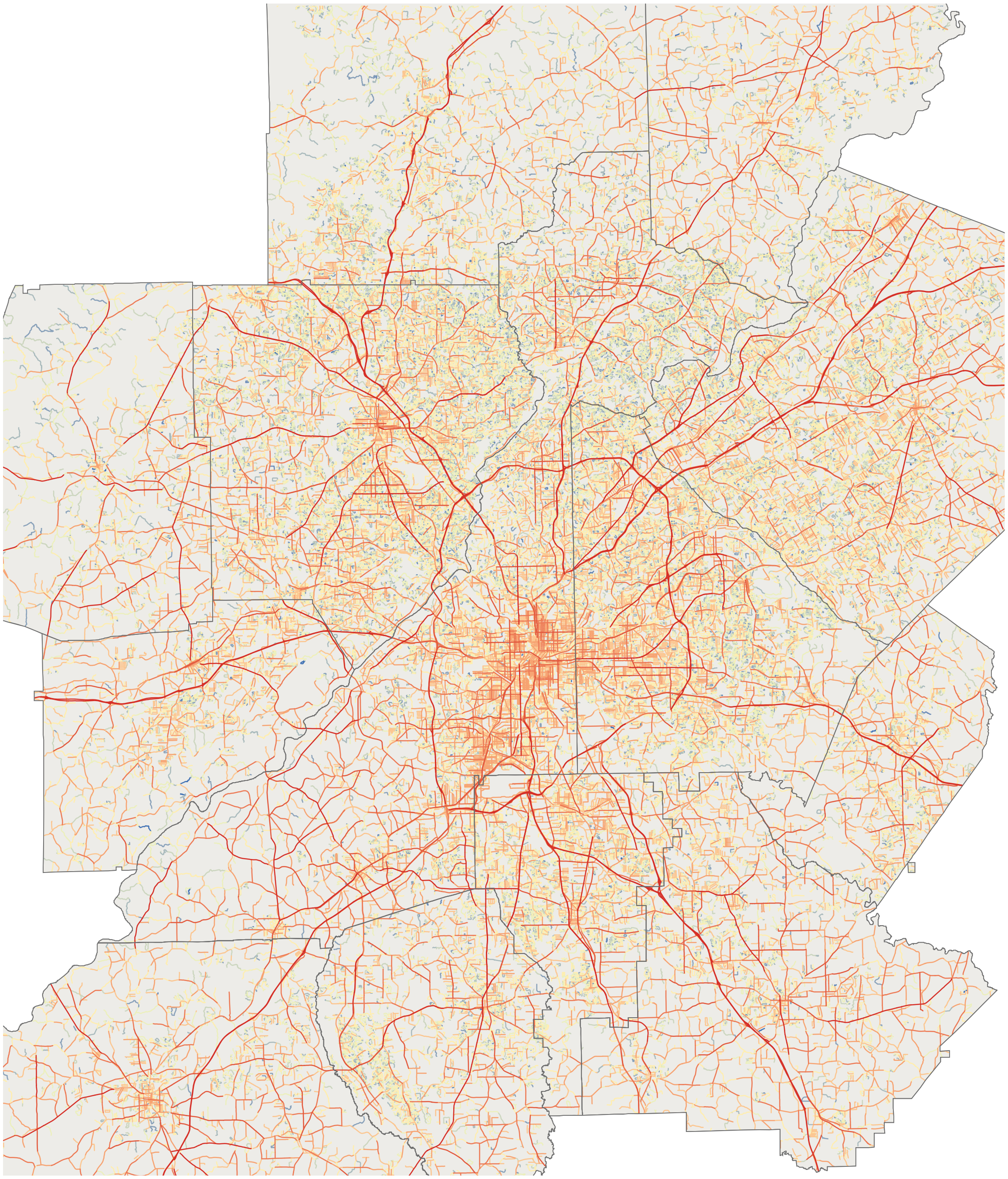

Figure 61: Diagram of directional reach with zero turns on all roads. Blue roads have the lowest reach value, and red roads have the highest.

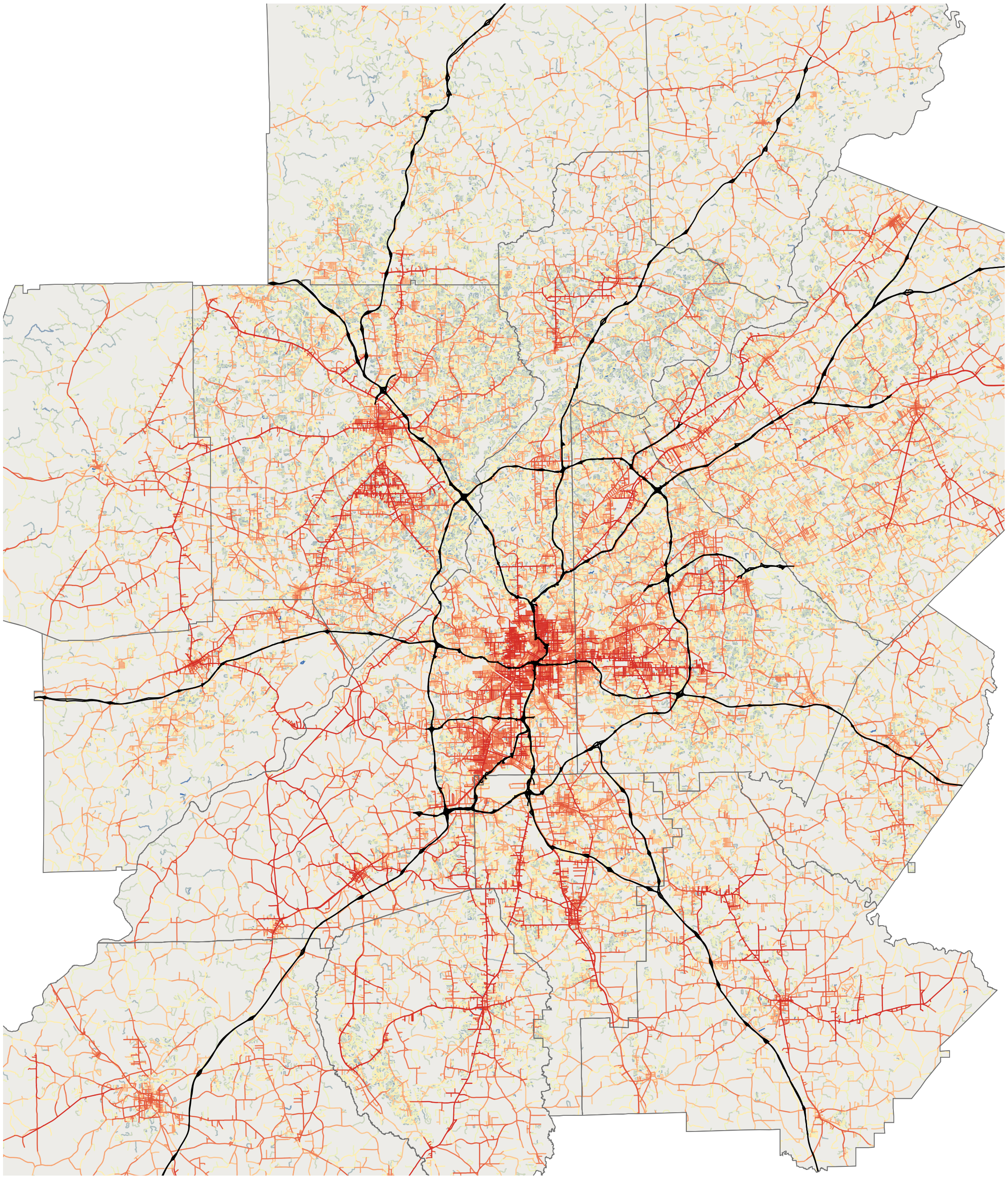

Figure 62: Diagram of directional reach with two turns on non-freeway roads. Blue roads have the lowest reach value, and red roads have the highest.

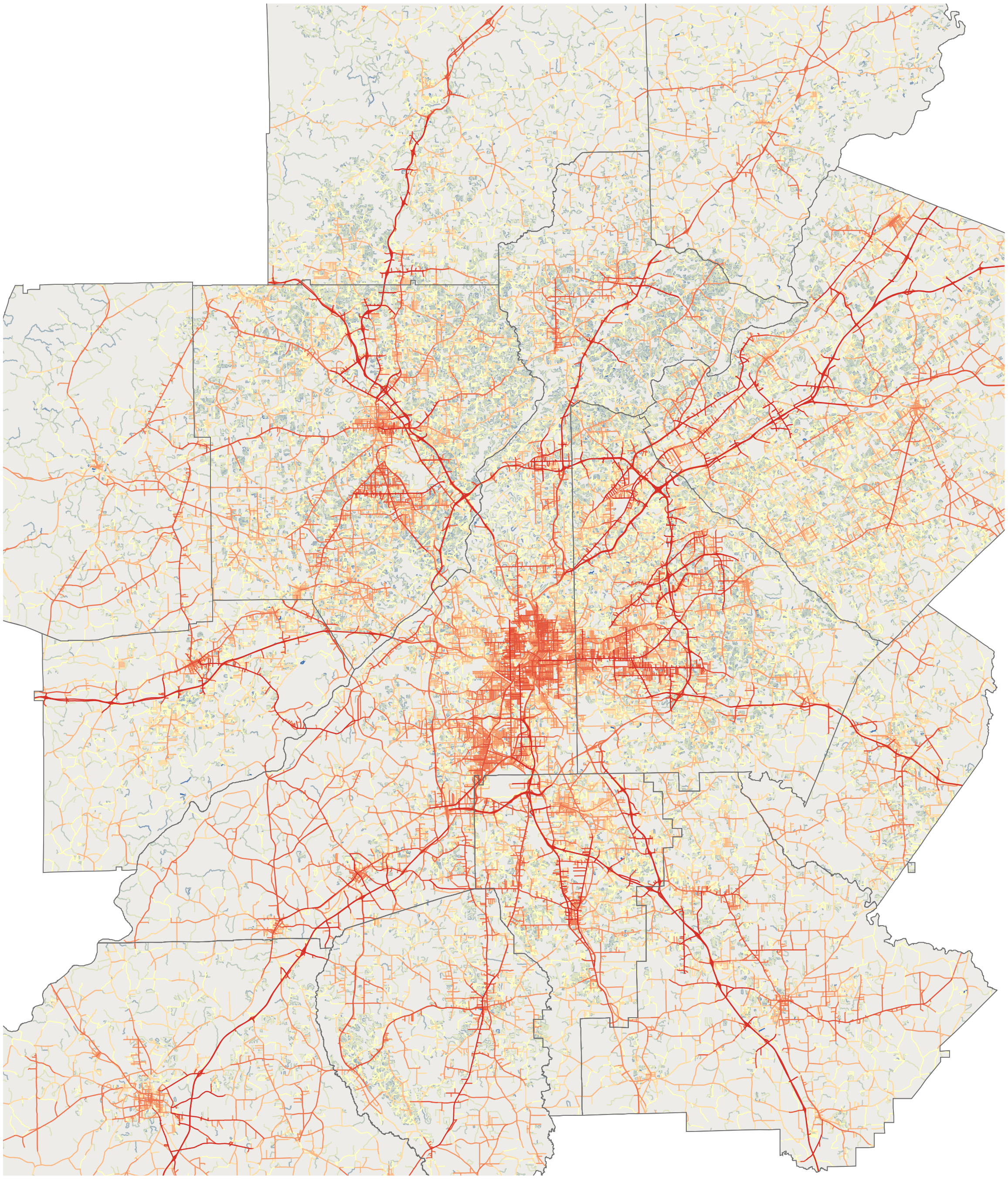

Figure 63: Diagram of directional reach with two turns on all roads. Blue roads have the lowest reach value, and red roads have the highest.

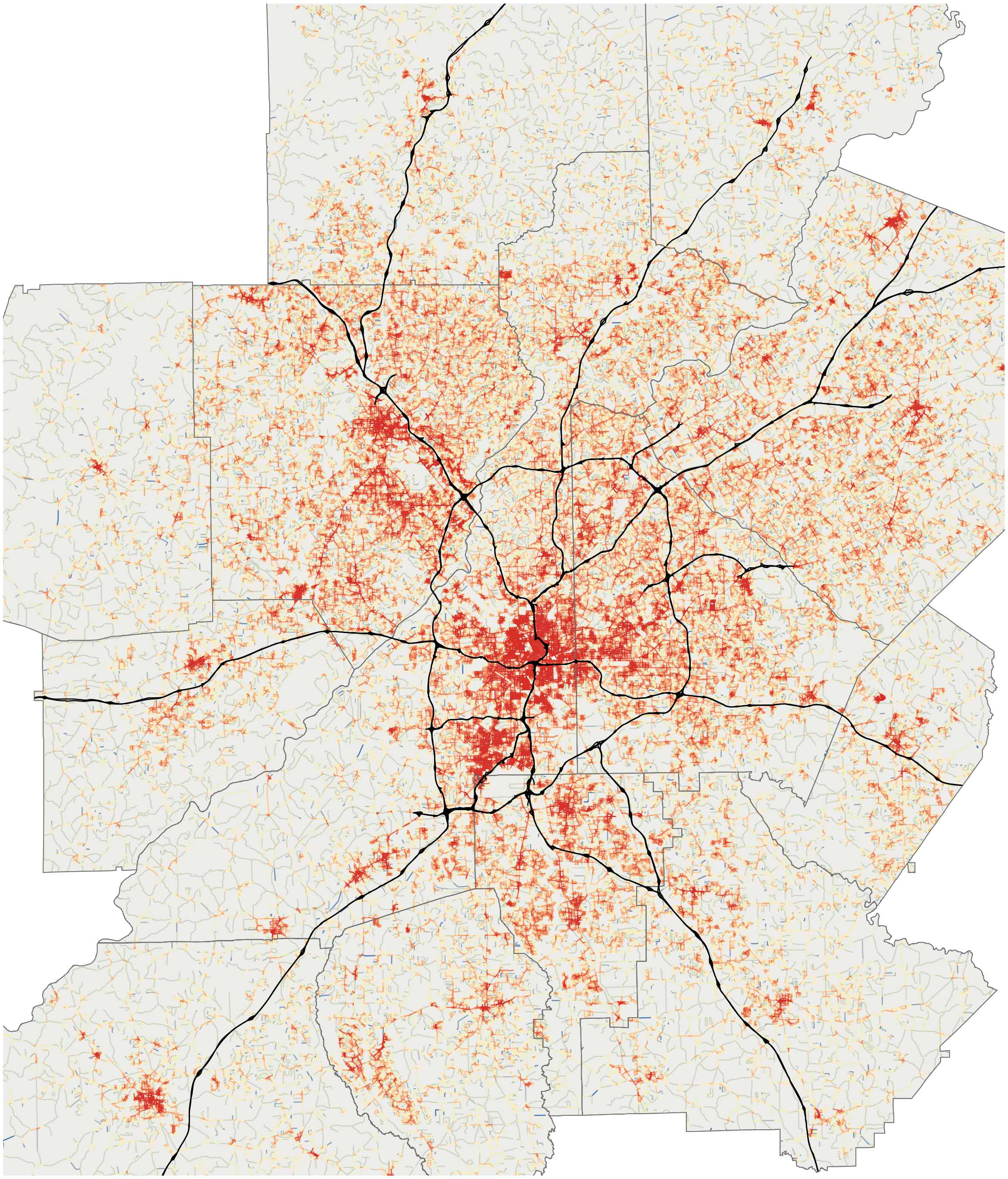

Figure 64: Diagram of metric reach with a radius of 0.25 miles on non-freeway roads. Blue roads have the lowest reach value, and red roads have the highest.

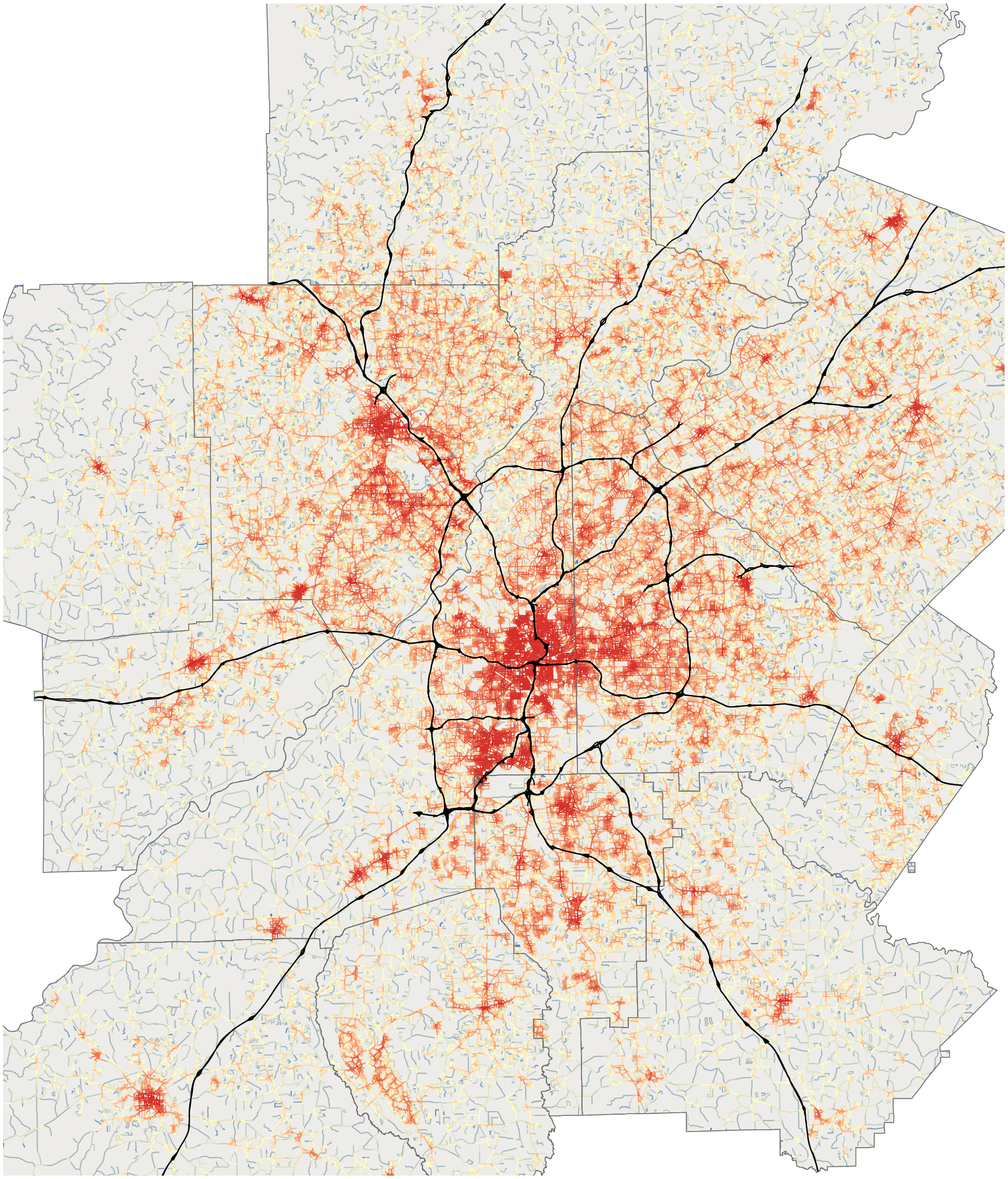

Figure 65: Diagram of metric reach with a radius of 0.50 miles on non-freeway roads. Blue roads have the lowest reach value, and red roads have the highest.

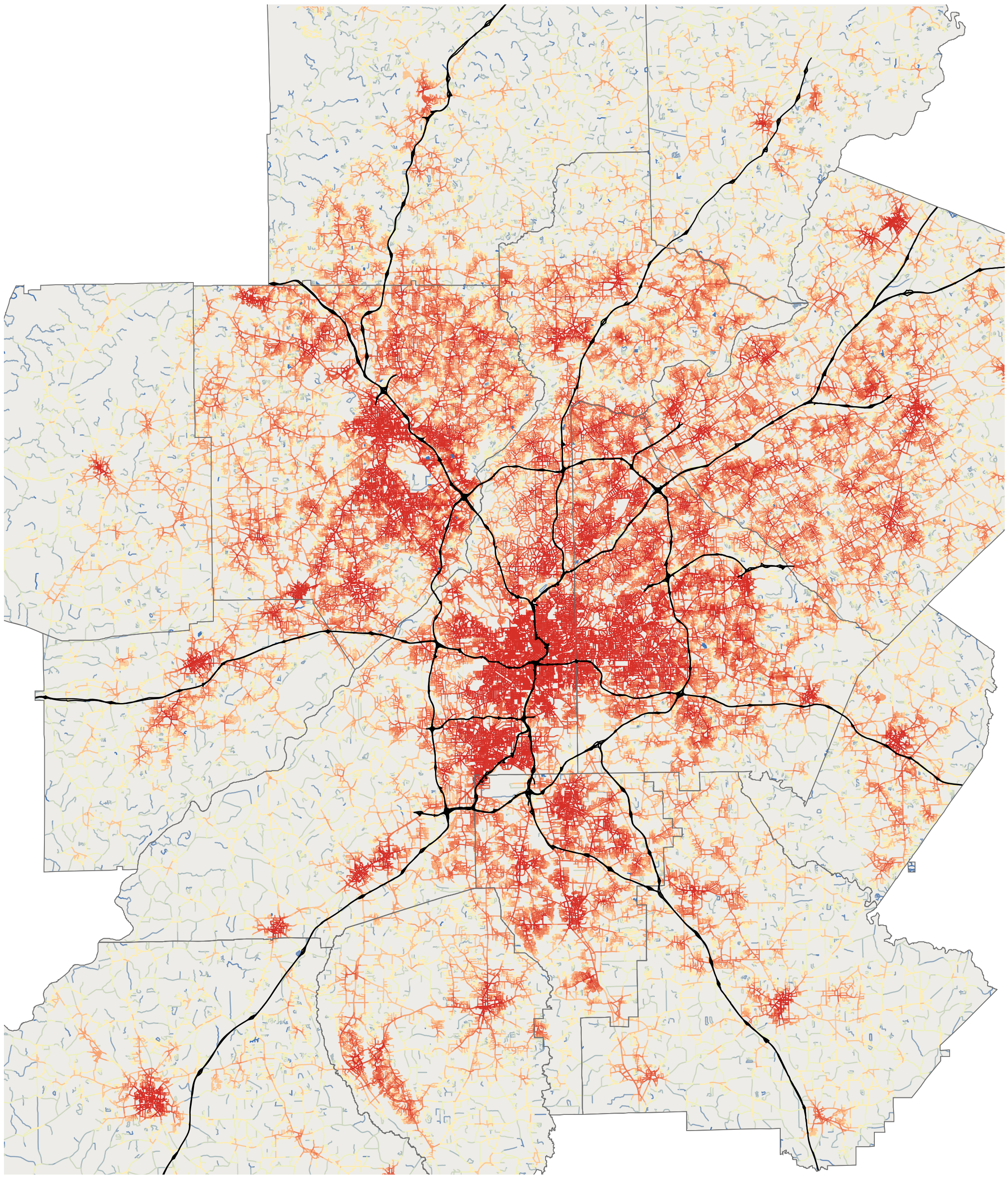

Figure 66: Diagram of metric reach with a radius of 1.0 miles on non-freeway roads. Blue roads have the lowest reach value, and red roads have the highest.

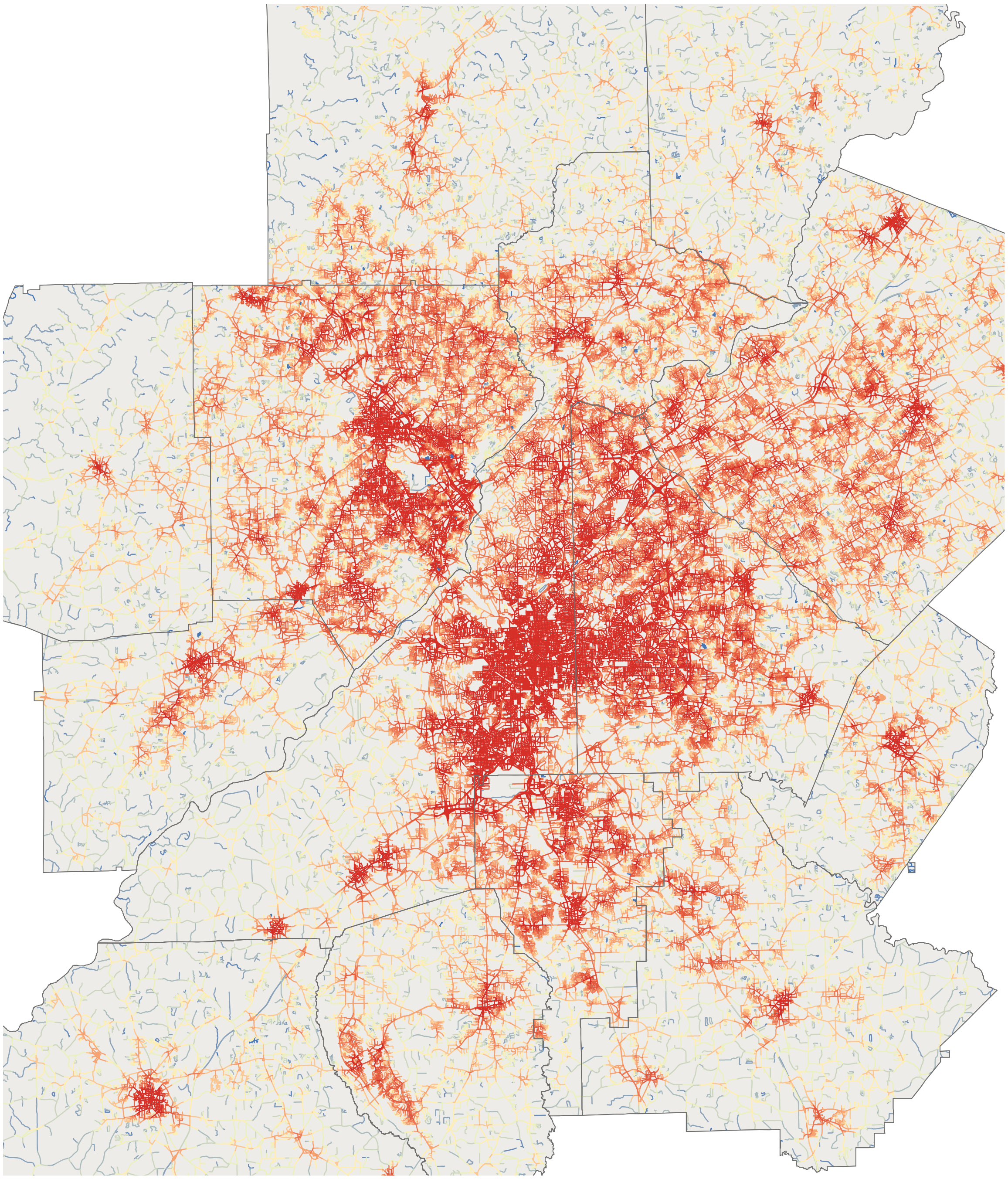

Figure 67: Diagram of metric reach with a radius of 1.0 miles on all roads. Blue roads have the lowest reach value, and red roads have the highest.

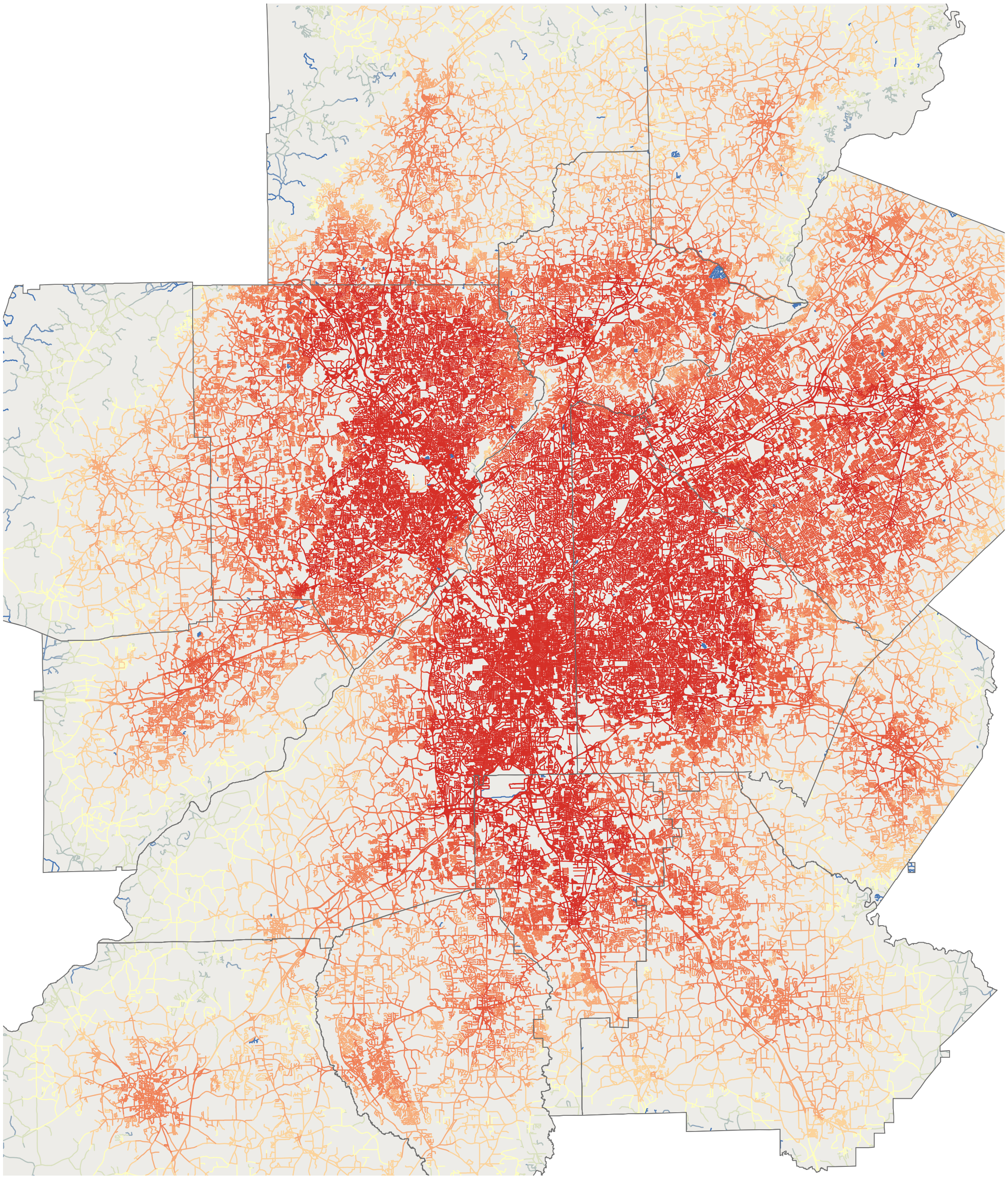

Figure 68: Diagram of metric reach with a radius of 5.0 miles on all roads. Blue roads have the lowest reach value, and red roads have the highest.

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